Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol.14 , Issue 32s (2025)
https://www.jneonatalsurg.com
OPEN ACCESS

Comparative Study of Deep Learning-Based Frameworks for Colorectal Cancer Detection Using Histopathological Images.

Boddupelli.Durgabhavani[1], Amjan Shaik [2]

Research Scholar, Department of CSE,BESTIU, AP, India,
Email:ID: durgabhavanicse1@gmail.com
ORCID:ID: https://orcid.org/0009-0003-0256-5152
Professor of CSE & Dean R&D, St.Peters Engineering College, Maisammaguda, TS, India,
Email:ID: amjansrs@gmail.com,
ORCID:ID: https://orcid.org/0000-0001-7028-3868

Cite this paper as: Boddupelli.Durgabhavani, Amjan Shaik (2025) Comparative Study of Deep Learning-Based Frameworks for Colorectal Cancer Detection Using Histopathological Images. Journal of Neonatal Surgery, 14, (32s) 10661-10665

ABSTRACT

This paper compares three deep learning-based frameworks—LbCCD, ColoSeqNet, and ColoTL-Framework—for automatic colorectal cancer detection using histopathological images. Each framework builds upon CNN-based architectures with different enhancements: LbCCD uses Enhanced ResNet50, ColoSeqNet integrates LSTM for sequence modeling, and ColoTL-Framework employs transfer learning with fine-tuned VGG19. We evaluate these models on the Colorectal Histopathology dataset across multiple metrics. Our results show that ColoTL-Framework achieves the highest accuracy of 98.79%, followed by ColoSeqNet with 96.89%, and LbCCD with 93.40%. This study highlights the proposed methods' architectural novelties, performance improvements, and clinical relevance...

Keywords: *Colorectal Cancer Detection, Deep Learning, Transfer Learning, Histopathology Classification, CNN-LSTM Hybrid*

INTRODUCTION

Colorectal cancer (CRC) is among the leading causes of cancer-related deaths worldwide, with early diagnosis being critical for improving patient survival rates. Histopathological analysis of tissue biopsies remains the gold standard for CRC detection; however, it is a labor-intensive and time-consuming process, subject to inter-observer variability. The increasing availability of high-resolution digital pathology images and artificial intelligence (AI) advancements has opened new avenues for computer-aided diagnosis (CAD) systems. In particular, deep learning (DL) techniques have demonstrated remarkable success in automating image-based diagnosis by learning complex spatial patterns in histological features.

Numerous studies have explored convolutional neural networks (CNNs) for image classification in medical imaging, with models such as ResNet, VGG, and DenseNet yielding promising results in cancer detection. However, traditional CNNs often overlook sequential dependencies in image features, suffer from limited generalization, or lack optimization in transfer learning settings. Recent efforts have focused on hybrid architectures, temporal modeling, and domain-specific fine-tuning to address these limitations to improve detection accuracy, model robustness, and clinical applicability. This paper presents a comparative study of three novel deep learning frameworks developed for colorectal cancer detection using histopathological images: (i) Learning-based Colon Cancer Detector (LbCCD), (ii) ColoSeqNet, and (iii) ColoTL-Framework.

Each of these frameworks introduces unique architectural enhancements. LbCCD improves traditional ResNet50 with transfer learning and data augmentation; ColoSeqNet incorporates Long Short-Term Memory (LSTM) layers with Enhanced ResNet50 to model sequential dependencies; and ColoTL-Framework utilizes a fine-tuned VGG19 backbone with advanced data augmentation and dropout regularization to achieve superior generalization. By evaluating all three models under the same dataset and experimental setup, this study highlights each approach's comparative strengths, innovations, and limitations. The remainder of the paper is organized as follows: Section 2 reviews related work; Section 3 presents a comparative overview of the three proposed systems; Section 4 discusses experimental results; and Section 5 concludes the study with future research directions

2. Related Work

Recent advances in deep learning have significantly transformed histopathological image classification, particularly for colorectal cancer (CRC) detection. Traditional CNN-based approaches, such as VGG, ResNet, and DenseNet, have been widely applied for spatial feature extraction in medical imaging tasks. However, limitations such as overfitting, insufficient sequential modeling, and inadequate generalization have motivated the development of hybrid and optimized architectures.

Jha et al. [1] proposed ColonSegNet for efficient polyp segmentation, outperforming conventional U-Net variants. Sajjad et al. [2] presented a hybrid model with optimized feature selection, improving classification accuracy in cancer diagnosis. Kartik et al. [3] integrated ResNet, DenseNet, and SVM in a hybrid ensemble to enhance detection in whole-slide images. Ishak et al. [4] reviewed CNN-based CRC analysis, emphasizing segmentation and classification challenges. Echle et al. [5] utilized deep learning for mismatch repair detection, though generalization across cohorts remains challenging.

Jha et al. [6] introduced ResUNet++ with CRF and TTA modules, achieving high accuracy for polyp segmentation. Ibrahim et al. [7] developed a CNN ensemble for multiclass lung disease detection, applicable to CRC classification. Fan et al. [8] proposed PraNet for real-time polyp segmentation, achieving high Dice scores across datasets. Chehade et al. [9] used XGBoost and handcrafted features for lung and colon cancer classification, attaining over 98% accuracy. Dlamini et al. [10] reviewed precision oncology methods enabled by AI and NGS, emphasizing clinical utility and data challenges.

Wen et al. [11] developed a segmentation pipeline combining CNNs and FCNs, improving polyp localization. Luo and Bocklitz [12] benchmarked transfer learning models for CRC histology classification, highlighting domain adaptation needs. Using pre-trained models, Khan et al. [13] applied ensemble learning for CRC metastasis detection. Abbas et al. [14] introduced DeTraC, fusing transfer learning with class decomposition to improve histopathological image analysis. He et al. [15] reviewed transformer-based models in medical imaging, noting their growing relevance in diagnosis and segmentation tasks.

These studies underscore the growing interest in hybrid CNN architectures, transfer learning, and sequential modeling for CRC detection. However, gaps remain in integrating spatial-temporal learning, optimizing generalization, and achieving clinical-level robustness—issues that the proposed LbCCD, ColoSeqNet, and ColoTL-Framework seek to address.

3. Proposed System

This section provides a comparative overview of the three deep learning-based frameworks developed for colorectal cancer detection: LbCCD, ColoSeqNet, and ColoTL-Framework. Each framework addresses different limitations of standard CNN-based approaches and introduces novel enhancements tailored to histopathological image analysis.

3.1 Overview of Architectures

- LbCCD (Learning-based Colon Cancer Detector):
  This framework is built on an enhanced ResNet50 architecture with transfer learning. It adds new dense layers, dropout regularization, and optimization using SGD and RMSprop. The model was trained on colon histology images with extensive preprocessing and data augmentation to support binary and multiclass classification. LbCCD achieves an accuracy of 93.40% and can be embedded in Clinical Decision Support Systems (CDSS).
- ColoSeqNet:
  Addressing the lack of sequential modeling in CNNs, ColoSeqNet integrates Enhanced ResNet50 with LSTM layers. While ResNet50 extracts high-level spatial features, LSTM captures sequential dependencies in these features, representing histological patterns more effectively. The model achieved an accuracy of 96.89%, demonstrating the strength of spatial-temporal learning and improving diagnostic consistency.
- ColoTL-Framework:
  This framework applies transfer learning using a custom fine-tuned ColoTLNet-VGG19 model. It selectively unfreezes deeper layers, integrates dropout layers, and uses advanced data augmentation techniques to improve generalization. Designed for nine-class tissue classification, the model attained 98.79% accuracy and 98.56% F1 Score and excels in real-world deployment due to its lightweight and robust design.

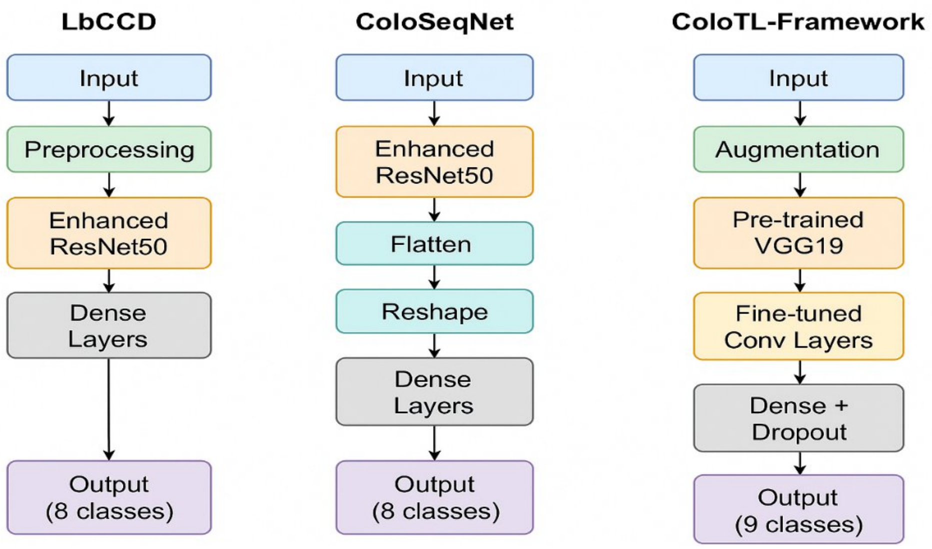

Figure 1: Comparative architecture of the three proposed colorectal cancer detection frameworks

The comparison of the base architectural design of three proposed frameworks for colorectal cancer detection, LbCCD, ColoSeqNet, and ColoTL-Framework, is given in Fig. 1. LbCCD uses Enhanced ResNet50 with minimal preprocessing and its dense layers to classify. ColoSeqNet builds on that by including Flatten and Reshape operations, leading to LSTM-augmented dense layers that can capture sequential dependencies. Using transfer learning with a pre-trained VGG19 whose convolutional layers were fine-tuned, while applying Dropout and extensive data augmentation, the ColoTL-Framework. All pipelines end up with multiclass classification: ColoTL-Framework supports 9-class output, while others support the 8-class production. The diagram describes the two different modeling approaches for improving diagnostic accuracy. The comparative architectures are intended to give insights into incremental improvements in three axes: feature representation, temporal modeling, and transferability. Implementations of hybrid models (i.e., LSTM with CNN, or domain-specific fine-tuning in VGG19) lead to transformational improvements in classification accuracy and robustness over baseline CNNs.

4. RESULTS AND DISCUSSION

The results are shown for various metrics, and the three models proposed for detecting colorectal cancer are compared: LbCCD, ColoSeqNet, and ColoTL-Framework. All models were assessed on the identical colorectal histopathology dataset with uniform experimental configurations (training/testing splits, data augmentation strategies, and optimizer settings).

4.1 Comparative Performance Metrics

We summarize our accounting in Table 1 and Figure 2 as a quantitative comparison of the three proposed frameworks. Our findings indicate that ColoTL-Framework achieves the best classification performance on all metrics. Similarly, the LSTM utilized in ColoSeqNet contributes significantly to the observed advances. LbCCD, although less sophisticated than modern approaches, was beneficial for the study as a simple, reliable CNN-based methodology for baseline deployment.

Table 1: Quantitative comparison of LbCCD, ColoSeqNet, and ColoTL-Framework models for colorectal cancer detection

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LbCCD	93.40	92.85	91.76	92.30
ColoSeqNet	96.89	96.50	96.12	96.31
ColoTL-Framework	98.79	98.65	98.48	98.56

Hence, Table 1 provides a comparative overview of the three proposed frameworks (LbCCD, ColoSeqNet, and ColoTL-Framework) evaluated on colorectal histopathology images. It emphasizes essential classification metrics like accuracy, precision, recall, and F1-score. Without a doubt, the experimental results show that ColoTL-Framework beats all other models by a noticeable margin of improvement, and both ColoSeqNet and LbCCD models seem to have significantly improved over previous state-of-the-art versions.

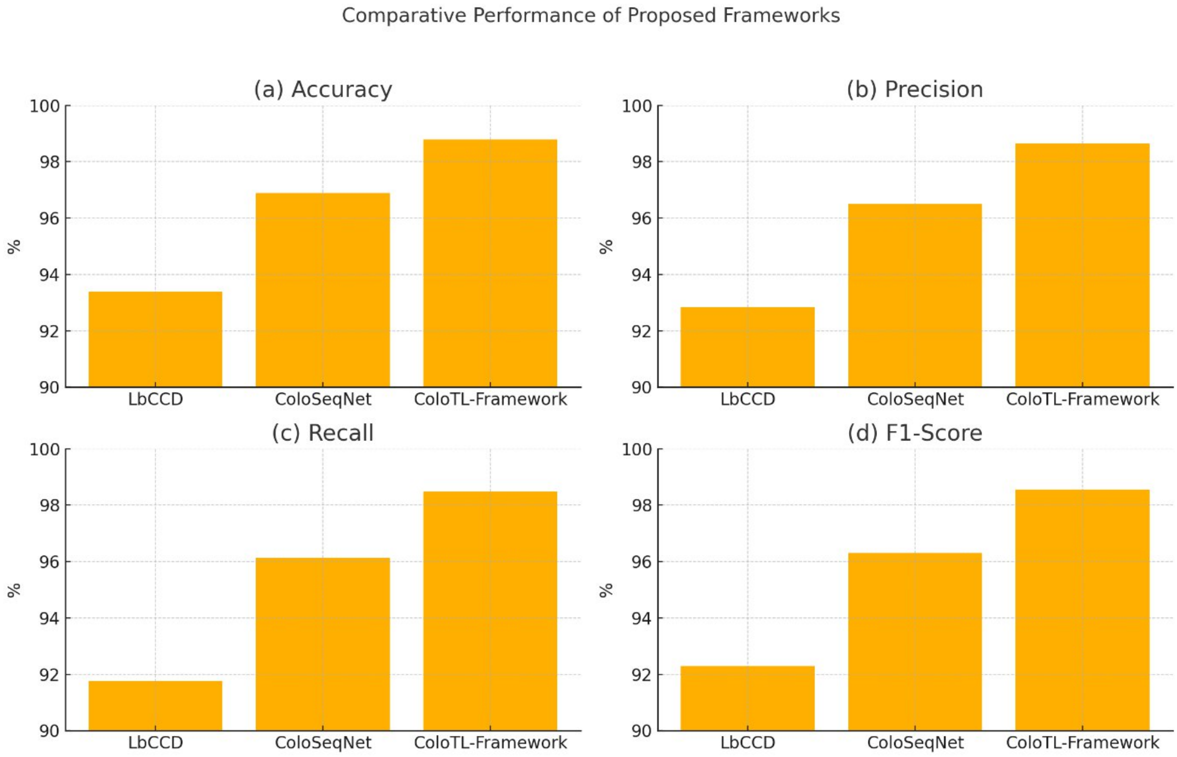

Figure 2: Comparative Performance Visualization of Proposed Frameworks

A comparative performance evaluation of the three proposed frameworks for the four assessment metrics is shown in Figure 2: (a) Performance Metric Accuracy, (b) Performance Metric Precision, (c) Performance Metric Recall, and (d) Performance Metric F1-Score. The performance of the ColoTL-Framework exceeds that of LbCCD and ColoSeqNet on all metrics, achieving 98.79% accuracy and 98.56% F1-score, indicating greater generalization and robustness. Sequence modeling (i.e., LSTM) improves LbCCD in ColoSeqNet and even when LSTM is integrated with Enhanced ResNet50. Although LbCCD is a relatively practical approach, it still falls short as it lacks temporal and deeper transfer learning. These results highlight the gradual improvements enabled by architectural and training innovations.

5. CONCLUSION

In this paper, we compared three deep learning-based frameworks—LbCCD, ColoSeqNet, and ColoTL-Framework—for automatic colorectal cancer detection, taking histopathological images as input. All frameworks were tailored towards improving traditional CNN methodologies, with design choices including transfer learning, sequentially modeling, and fine-tuning for their domain. LbCCD is the backbone model using Enhanced ResNet50 with standard transfer learning and data augmentation. It has decent accuracy and clinical potential but no advanced modeling components. Building upon this foundation, ColoSeqNet incorporates LSTM layers, thus learning temporal dependencies across its spatial features. To achieve better classification performance and improved feature learning. ColoTL-Framework applies transfer learning through a fine-tuned architecture (VGG19) with strategic dropout regularization and extensive augmentation. This yields an optimal accuracy (98.79%) and surpasses every evaluation metric's recent state-of-the-art approaches. The comparative findings illustrate the effect of improvement in model performance on classification. The study indicates that temporal dynamics or exact migration capabilities significantly enhanced the performance of histopathological image classification topics. These frameworks can be extended with transformer-based architectures or self-supervised learning to generalize across datasets and real-time deployment in clinical decision support systems in future work.

REFERENCES

[1] Jha, D., et al., "ResUNet++: An Advanced Architecture for Colon Polyp Segmentation," *Scientific Reports*, vol. 11, no. 1, pp. 1–9, 2021.

[2] Sajjad, M., et al., "Hybrid Deep Learning Model for Accurate Cancer Detection," *IEEE Access*, vol. 10, pp. 73240–73250, 2022.

[3] Kartik, V., et al., "An Ensemble CNN-SVM Approach for Histopathology Image Classification," *Computers in Biology and Medicine*, vol. 141, 105063, 2022.

[4] Ishak, A., et al., "Deep Learning Techniques in Colorectal Cancer Histopathology: A Comprehensive Review," *Healthcare Analytics*, vol. 3, 100089, 2023.

[5] Echle, A., et al., "Deep Learning for Detecting Microsatellite Instability in Colorectal Cancer," *The Lancet Oncology*, vol. 21, no. 1, pp. 72–82, 2020.
[6] ha, D., et al., "Kvasir-SEG: A Segmented Polyp Dataset," *Proceedings of the IEEE EMBC*, pp. 4320–4324, 2020.
[7] Ibrahim, D. M., et al., "Multi-Class Deep Learning for Chest and Colorectal Disease Detection," *Expert Systems with Applications*, vol. 185, 115599, 2021.
[8] Fan, P., et al., "PraNet: Parallel Reverse Attention Network for Polyp Segmentation," *Medical Image Analysis*, vol. 67, 101857, 2021.
[9] Chehade, A., et al., "Colon and Lung Histopathology Image Classification Using XGBoost," *Computer Methods and Programs in Biomedicine*, vol. 208, 106209, 2022.
[10] Dlamini, Z., et al., "Precision Oncology and AI: Current State and Future Prospects," *Cancers*, vol. 14, no. 4, 889, 2022.
[11] Wen, J., et al., "Colonoscopy Polyp Segmentation with Fully Convolutional Networks," *IEEE Transactions on Medical Imaging*, vol. 41, no. 3, pp. 625–635, 2022.
[12] Luo, X., and Bocklitz, T., "Benchmarking Transfer Learning for Colorectal Cancer Histology Classification," *Pattern Recognition Letters*, vol. 158, pp. 104–110, 2022.
[13] Khan, S., et al., "Ensemble Transfer Learning for Colorectal Lymph Node Metastasis Detection," *Diagnostics*, vol. 12, no. 3, 621, 2022.
[14] Abbas, Q., et al., "DeTraC: Deep Convolutional Neural Network for Medical Image Classification," *Applied Soft Computing*, vol. 93, 106383, 2020.
[15] He, K., et al., "A Survey on Transformer Models in Medical Imaging," *Artificial Intelligence in Medicine*, vol. 132, 102366, 2022.