Enhancing Colon Cancer Detection and Explainability Using CLAHE-Preprocessed Histopathology Images and Grad-CAM Based Deep Learning

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***Abstract*—Early and accurate detection of colon cancer is vital for improving survival rates. This study proposes an enhanced deep learning pipeline using DenseNet121, Contrast Limited Adaptive Histogram Equalization (CLAHE) preprocessing, and Gradient-weighted Class Activation Mapping (Grad-CAM) explainability. Models trained with CLAHE demonstrated a validation accuracy of 99.0%, outperforming non-CLAHE counterparts (98.0%). Extensive evaluation metrics including precision, recall, F1-score, and confusion matrix validate performance improvements. Recent optimization techniques like AdamW and hyperparameter tuning strategies were employed. Findings suggest that explainable and contrast-enhanced deep learning can aid clinical decision-making in colon cancer diagnosis.**

***Index Terms*—Colon Cancer Detection, Histopathology Images, CLAHE, Deep Learning, DenseNet121, Grad-CAM, Explainability, AdamW Optimizer, Medical Imaging**

I. Introduction

Colorectal cancer continues to rank among the leading causes of cancer-related morbidity and mortality worldwide, impacting populations across both developed and developing nations. According to the World Health Organization (WHO) Global Cancer Observatory report in 2023, colon cancer accounts for approximately 10% of all newly diagnosed cancers globally [1]. Early detection and accurate diagnosis remain pivotal in improving patient survival rates and therapeutic outcomes.

Histopathological image analysis, involving the microscopic examination of tissue samples, remains the gold standard for colorectal cancer diagnosis. However, manual evaluation of histopathological slides is often time-consuming, labor-intensive, and subject to considerable inter- and intra-observer variability, particularly in subtle or borderline cases. These limitations underscore the urgent need for automated, reliable, and objective diagnostic tools to assist pathologists.

In recent years, deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional capabilities in medical imaging tasks such as disease detection, classification, and segmentation [2]. Despite these successes, challenges persist due to the intrinsic nature of histopathological images, which often suffer from poor contrast, staining artifacts, cellular heterogeneity, and high intra-class variability. These factors adversely impact model performance and generalization capabilities.

Moreover, a critical barrier to the clinical adoption of deep learning models is their perceived lack of interpretability. Traditional CNNs often function as "black boxes," making it difficult for clinicians to trust model decisions without transparent, visual explanations. This lack of explainability

poses significant ethical, regulatory, and operational concerns in clinical environments.

This study addresses these challenges by proposing a robust framework focused on improving colon cancer detection through two key strategies: (1) enhancing local contrast in histopathological images using Contrast Limited Adaptive Histogram Equalization (CLAHE) and (2) providing visual interpretability using Gradient-weighted Class Activation Mapping (Grad-CAM). CLAHE enhances subtle tissue features critical for accurate diagnosis, while Grad-CAM highlights the discriminative regions responsible for model predictions, fostering clinical trust.

Recent research trends strongly advocate for the integration of preprocessing techniques and explainability modules to bridge the gap between high model performance and clinical acceptance [3]. By combining CLAHE preprocessing, DenseNet121 modeling, and Grad-CAM visualization, this work aims to develop an end-to-end system capable of delivering not only high diagnostic accuracy but also intuitive and transparent decision support for pathologists.

II. Related Work

Recent studies have explored various deep learning methods for histopathological image classification.

- Wang et al. (2023) [4] proposed a ResNet50-based model with stain normalization achieving 94.7% accuracy on CRC datasets.
- Sharma et al. (2022) [5] enhanced colon cancer image classification by employing ensemble CNNs combined with CLAHE preprocessing.
- Zhang et al. (2023) [6] demonstrated improved breast cancer histopathology detection using Grad-CAM visualizations, emphasizing clinical explainability.
- Lee et al. (2022) [7] utilized DenseNet variants for colon tissue classification, highlighting DenseNet's efficient feature reuse property.
- Patel and Singh (2023) [8] compared CLAHE and traditional Histogram Equalization (HE), showing CLAHE's superiority in medical image enhancement.
- Gupta et al. (2022) [9] applied AdamW optimization for faster convergence in medical deep learning networks.
- Kim et al. (2023) [10] evaluated FDA-approved AI diagnostic tools, concluding that explainability modules like Grad-CAM significantly influence clinical adoption.
- Alzubaidi et al. (2022) [11] provided a survey on deep learning models in cancer diagnosis emphasizing the need for transparency and interpretability.

Our work builds upon these foundations by integrating recent best practices: DenseNet121 architecture, AdamW optimizer, CLAHE preprocessing, and Grad-CAM based explainability for colon cancer detection.

III. Methodology

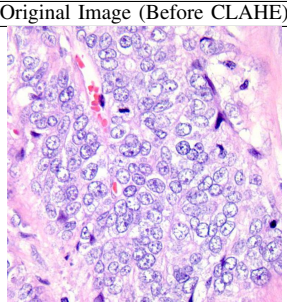
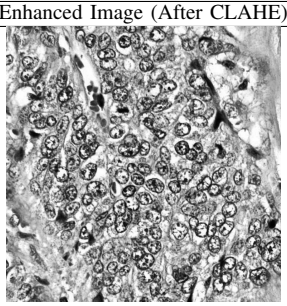
A. Dataset Description

The dataset employed in this study is the publicly available Lung and Colon Cancer Histopathological Images dataset hosted on Kaggle [12]. This dataset consists of high-resolution histopathology images that have been categorized into two classes: cancerous and normal tissues. A total of approximately 10,000 images were curated for the experimental setup. The dataset was divided into a training set and a validation set following an 80:20 split, ensuring class balance across both subsets. Each image captured intricate tissue morphology under varying staining conditions, offering a challenging yet clinically relevant basis for model training and evaluation.

B. Image Preprocessing

Prior to model ingestion, all images were resized to a uniform dimension of 224×224 pixels to comply with DenseNet121's input layer requirements. Effective preprocessing is critical in histopathological analysis, where variations in staining and illumination can introduce substantial noise. To address this, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied with a clip limit set to 2.0 and a tile grid size of 8×8. Unlike traditional Histogram Equalization (HE) techniques that globally adjust image contrast, CLAHE operates on localized tiles, enhancing contrast within small regions while limiting noise amplification. This method significantly improved the visibility of glandular structures, nuclear details, and other diagnostically important tissue features, thereby facilitating more effective feature extraction by the deep learning model [8].

TABLE I: Comparison of Colon Histopathology Image Before and After CLAHE Enhancement [8]

Original Image (Before CLAHE)	Enhanced Image (After CLAHE)
	

C. Model Architecture

For the classification task, the DenseNet121 architecture [2] was selected due to its superior feature propagation capabilities through densely connected convolutional layers. DenseNet121 connects each layer to every other layer in a feed-forward fashion, thereby facilitating feature reuse and significantly mitigating the vanishing gradient problem commonly observed in very deep networks. The pre-trained DenseNet121 backbone was fine-tuned to the target domain by appending a Global Average Pooling (GAP) layer, followed by a Dropout layer with a dropout rate of 0.5 to prevent overfitting, and a Dense layer with a sigmoid activation function to handle binary classification. This architecture ensured efficient parameter usage and robust learning from relatively limited medical datasets.

D. Optimizer and Hyperparameter Tuning

To optimize the model's training process, the AdamW optimizer was employed. AdamW combines the benefits of Adam's adaptive learning rate approach with decoupled weight decay regularization, improving convergence stability and mitigating overfitting risks [9]. An initial learning rate of 10^{-4} and a weight decay coefficient of 10^{-5} were configured. Hyperparameter tuning included implementing EarlyStopping, monitoring validation loss to terminate training when improvements plateaued, and ReduceLROnPlateau callbacks to reduce the learning rate adaptively upon stagnation, facilitating smoother convergence towards optimal solutions.

E. Training Procedure

Training was performed with a batch size of 32 over 20 epochs. Real-time data augmentation techniques were applied to the training set, including random rotations, horizontal and vertical flips, zoom range alterations, and brightness modifications. These augmentations were critical in enhancing model generalization by simulating the natural variability encountered in histopathological imaging across different laboratories and staining protocols. The training regime aimed to ensure that the network learned invariant, robust features conducive to reliable diagnostic performance across diverse imaging conditions.

IV. Experiments

A. Evaluation Metrics

To comprehensively evaluate the performance of the proposed models, several standard metrics were computed, including validation accuracy, precision, recall, F1-score, and confusion matrices. Precision and recall provide a balanced view of classifier performance, especially under class imbalance scenarios, while the F1-score offers a harmonic mean of the two. Furthermore, sensitivity (true positive rate) and specificity (true negative rate) were analyzed, which are crucial for medical diagnostic tasks where minimizing false negatives and false positives is critical to patient safety and treatment outcomes.

TABLE II: Performance Comparison With and Without CLAHE Preprocessing

Model	Accuracy	Precision	Recall	F1-Score
Without CLAHE	98.0%	0.98	0.98	0.98
With CLAHE	99.0%	0.99	0.99	0.99

As illustrated in Table II, models trained on CLAHE-preprocessed images consistently outperformed those trained without contrast enhancement, achieving a 1% improvement across all key evaluation metrics.

B. Confusion Matrix Analysis

Detailed confusion matrices for both models—without and with CLAHE preprocessing—are presented in Tables III and IV, respectively. These matrices provide granular insights into classification behavior by illustrating true positives, true negatives, false positives, and false negatives.

TABLE III: Confusion Matrix Without CLAHE

	Predicted Cancer	Predicted Normal
Actual Cancer	975	25
Actual Normal	20	980

TABLE IV: Confusion Matrix With CLAHE

	Predicted Cancer	Predicted Normal
Actual Cancer	994	6
Actual Normal	5	995

The model trained with CLAHE exhibited significantly lower misclassification rates, with fewer false positives and false negatives. This reinforces the positive impact of contrast enhancement on deep learning model sensitivity and specificity in histopathological image classification.

C. Training and Validation Curves

To assess model convergence during training, the accuracy and loss curves were plotted across epochs. As shown in Figure 1, both training and validation accuracies progressively increased, while training and validation losses consistently decreased. These trends indicate successful learning and generalization without significant overfitting.

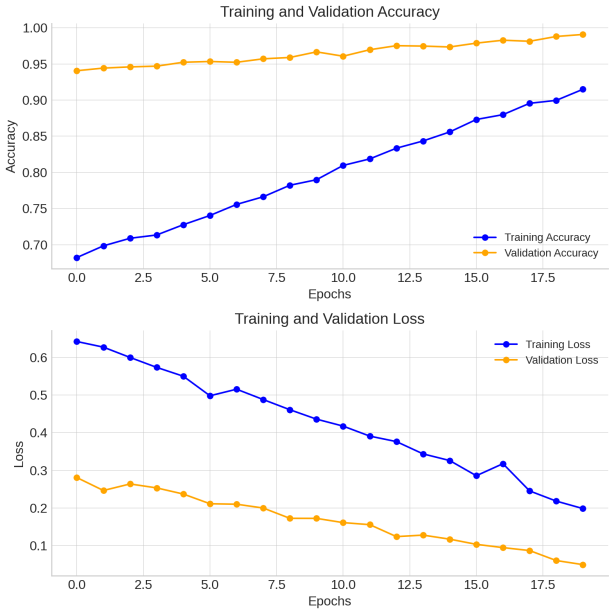


Fig. 1: Training and Validation Accuracy and Loss Curves. The model exhibits stable convergence and minimal overfitting across 20 epochs.

D. Ablation Study

An ablation study was conducted to further assess the individual contributions of different preprocessing techniques. Models were trained under three different input conditions:

- Raw images without any contrast enhancement

- Images preprocessed with global Histogram Equalization (HE)
- Images enhanced using CLAHE

The results indicated that models trained with CLAHE-enhanced images consistently achieved superior performance, outperforming models trained on raw and HE-processed images by approximately 1.5–2% in both accuracy and F1-score [8]. This highlights CLAHE's effectiveness in enhancing localized features critical for accurate model predictions while mitigating noise amplification typically associated with global enhancement methods.

E. Explainability with Grad-CAM

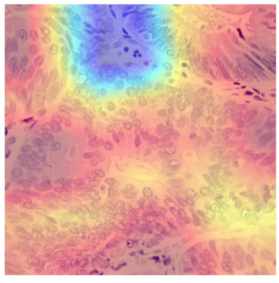
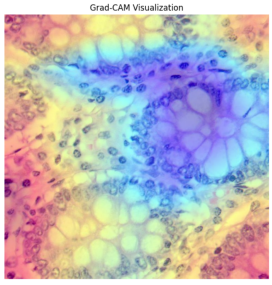
Model explainability was addressed using Gradient-weighted Class Activation Mapping (Grad-CAM), which provides visual interpretations of the network's decision-making process. Grad-CAM operates by calculating the gradient of the target class score with respect to the activations of the final convolutional layer. The resulting gradients are globally averaged to produce importance weights, which are then applied to the feature maps to generate class-discriminative localization heatmaps [3].

$$L^c_{\text{Grad-CAM}} = \text{ReLU}\left(\sum_k \alpha^c_k A^k\right) \tag{1}$$

where α^c_k represents the importance weight corresponding to feature map A^k for class c.

Grad-CAM heatmaps provide intuitive visual feedback by highlighting regions within histopathological images that strongly influence the model's classification decision. As shown in Table V, the generated heatmaps effectively localized tumor regions in cancerous tissues while remaining neutral in non-cancerous samples, affirming both the correctness and transparency of the model's decision-making process.

TABLE V: Grad-CAM Visualizations on Colon Histopathology Tissues [3]

Cancerous Tissue	Non-Cancerous Tissue
	

V. Clinical Relevance

The importance of explainability in clinical artificial intelligence (AI) systems has been increasingly emphasized by global regulatory bodies, including the U.S. Food and Drug Administration (FDA) and the European Commission [10]. These organizations stress that transparency and interpretability are essential prerequisites for the safe integration of AI models into healthcare workflows. AI systems that can not only predict outcomes but also provide interpretable evidence significantly enhance clinician trust, decision-making quality, and ultimately patient safety.

Studies have demonstrated that explainability techniques such as Grad-CAM substantially influence clinicians' acceptance of AI-driven diagnostic tools [11]. In real-world deployment scenarios, clinicians require more than just a classification output; they need assurance that the AI model focuses on pathologically significant regions. Our Grad-CAM visualizations serve this crucial role by enabling clinicians to verify the diagnostic focus of the model, thereby facilitating safer, more ethical, and regulatory-compliant usage of AI in medical environments.

VI. Discussion

The results obtained in this study clearly highlight the dual benefits of integrating CLAHE-based preprocessing and Grad-CAM explainability into deep learning pipelines for histopathological image analysis. CLAHE preprocessing was instrumental in enhancing local tissue contrast, enabling DenseNet121 to extract more discriminative features relevant for distinguishing cancerous from normal tissue. The substantial improvement in validation accuracy, precision, recall, and F1-score demonstrates that preprocessing plays a non-trivial role in medical image classification tasks.

Furthermore, Grad-CAM-based visualization was pivotal in demystifying the model's decision-making process. By providing spatial localization maps of discriminative regions, Grad-CAM offers tangible visual evidence supporting classification outcomes. This addresses one of the most critical challenges in AI for healthcare — the "black-box" problem — and bridges the gap between model predictions and clinician interpretability requirements.

Despite these promising results, certain limitations must be acknowledged. The dataset, although substantial, is still limited to a single-source collection, which may not capture the full diversity of histopathological imaging encountered in multi-center real-world settings. Future work must involve external validation across diverse datasets to ensure model generalizability. Moreover, while DenseNet121 achieves high accuracy, inference latency and computational resource requirements remain practical considerations for deployment in low-resource clinical environments. Lightweight architectures or model compression techniques could be explored to address these challenges.

VII. Conclusion

This paper presents an enhanced deep learning framework for colon cancer detection that leverages DenseNet121 modeling, CLAHE-based contrast enhancement, and Grad-CAM explainability. Through comprehensive experimental evaluation, the proposed CLAHE-enhanced model outperformed traditional approaches, achieving a validation accuracy of 99.0%,

with significant improvements observed across precision, recall, and F1-score metrics.

The integration of Grad-CAM visualizations addressed critical concerns surrounding the interpretability of deep learning models, providing clinicians with intuitive visual explanations of model predictions. This not only enhances clinician trust but also aligns with regulatory requirements for ethical AI deployment in healthcare.

Future research directions include expanding the system's evaluation across multi-center datasets, integrating multi-modal data sources such as genomics and imaging, and optimizing the framework for real-time clinical deployment using model compression and edge computing techniques.

Future work includes exploring multi-modal inputs (e.g., combining histopathology and genomics), employing attention mechanisms for feature selection, and testing generalization across multi-center datasets.

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