

Selective RGB Channel Jittering for Robust Endoscopic Disease Detection Across Multiple Lesion Types

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ABSTRACT

Deep learning has significantly advanced medical image analysis, particularly in the field of endoscopic images. However, these advancements are constrained by the availability of high-quality, annotated medical datasets. This study examines the effect of selective RGB channel jittering as a targeted data augmentation strategy to improve multi-pathological disease detection in endoscopic images. The proposed approach applies channel-specific Gaussian noise to individual RGB channels, implements transfer learning using two different architectures, and evaluates performance across four gastrointestinal conditions: erosion, polyp, tumor, and ulcer from the MedFMC dataset. To prove robustness, the results demonstrate that blue channel jittering consistently improves detection performance by up to 2.7% in accuracy and 3.05% in F_1 across all pathologies, while red and green channel jittering significantly degrade performance. This degradation when jittering red and green channels indicates that these channels contain critical discriminative information for gastrointestinal pathology detection, while blue channel enhancement acts as effective regularization. These findings offer important insights for developing targeted data augmentation strategies in medical image analysis.

Keywords: Medical Image Analysis, Endoscopic Disease Detection, Data Augmentation, Channel Jittering, Transfer Learning

1. Introduction

Medical image analysis has undergone a revolutionary transformation through the integration of deep learning technologies, fundamentally changing how pathological conditions are detected and classified in clinical settings. The rapid advancement of convolutional neural networks (CNNs) has enabled the automated recognition of complex patterns in medical imagery, achieving diagnostic accuracy that rivals and sometimes exceeds that of human experts across multiple specialties. However, the success of these deep learning models is critically dependent on the availability of large, diverse, and high-quality annotated datasets. In medical imaging, obtaining such datasets is challenging due to privacy concerns, the high cost of data acquisition, and the requirement for expert annotations [11].

The global burden of gastrointestinal diseases continues to escalate, with these conditions representing a substantial portion of worldwide morbidity and mortality [2, 17]. Gastrointestinal cancers alone account for a significant percentage of cancer-related deaths globally, making early detection through advanced diagnostic methods crucial for improving patient outcomes. Traditional diagnostic approaches, while effective, face limitations including inter-observer variability, fatigue-related errors, and the subjective nature of visual interpretation. Early detection through endoscopic examination significantly improves patient outcomes, making the development of computer-aided diagnostic tools for endoscopic images a critical research priority.

Data acquisition in medical imaging presents unique obstacles that distinguish it from other computer vision domains. The challenges include stringent privacy regulations that limit data sharing, the substantial costs associated with obtaining high-quality medical images, and the absolute necessity for expert annotations by qualified medical professionals. Traditional augmentation methods, including geometric transformations such as rotation, scaling, and flipping, as well as intensity adjustments for brightness and contrast, provide general robustness improvements. However, these conventional techniques may not adequately capture the specific characteristics and diagnostic challenges inherent to medical images, particularly in the complex domain of endoscopic imaging for gastrointestinal disease detection [16].

Endoscopic images present unique challenges that set them apart from conventional photographic data. These include highly variable lighting conditions within the gastrointestinal tract, surface reflections from mucous membranes, and the presence of bodily fluids that significantly affect the color properties and visual characteristics of the captured images [3]. Standard

RGB images encode information across three distinct color channels (red, green, and blue), each potentially carrying different levels of discriminative information crucial for accurate pathological detection. The recent emergence of advanced CNN architecture specifically designed for medical applications has demonstrated exceptional performance across various medical imaging tasks. Li et al. (2024) demonstrated that deep learning approaches in endoscopic image processing have achieved remarkable accuracy improvements [27], with CNN-based systems successfully automating medical image analysis while alleviating physician workload and enabling more personalized patient care approaches.

Recent developments in deep learning for medical image analysis have shown promising results across multiple gastrointestinal pathologies [6, 21]. Domain-specific data augmentation techniques have shown satisfying performance compared to traditional approaches in medical imaging applications [4, 28]. While prior work has explored generic color augmentations in histopathology images [20, 29], the differential impact of jittering individual RGB channels on endoscopic disease detection remains unexplored. Selective channel jittering represents a targeted approach to data augmentation, introducing controlled noise to specific color channels and offering a more nuanced method for enhancing model robustness in medical imaging applications. This technique leverages the differential importance of color information across RGB channels in medical images, where different wavelengths may capture distinct pathological features. Color channel-specific analysis in medical imaging has revealed meaningful differences in diagnostic utility. For example, in ophthalmic fundus imaging, the green channel frequently offers superior contrast and feature discrimination, particularly for blood vessel segmentation and lesion identification, compared to the red or blue channels [30]. Similarly, in histopathological contexts, studies have demonstrated that distinct color channels or transformations (such as individual examination of RGB, HSV, or other color spaces) can affect classification performance, depending on the tissue type and staining conditions [29]. Despite significant progress in deep learning applications for medical imaging, particularly in endoscopic analysis, notable gaps remain regarding the most effective augmentation strategies for diverse gastrointestinal conditions. While multiple augmentation methods have proven beneficial, few studies systematically assess how modifying individual color channels (e.g., R, G, B) influences diagnostic performance across multiple pathologies. Most existing research focuses on single-disease detection or employs general augmentation pipelines without examining the specific contribution of color-channel manipulations [7, 31].

Recent advances in convolutional neural networks (CNNs) have established robust foundations for exploring the effectiveness of channel-specific augmentation strategies in medical imaging. CNN-based models, owing to their ability to learn spatial and spectral features hierarchically, remain the predominant choice for automated disease detection and classification across diverse imaging modalities [11, 32]. The integration of transfer learning, where pre-trained CNN models on large-scale datasets such as ImageNet are fine-tuned for medical applications, has further accelerated progress by enabling effective knowledge transfer while reducing the need for extensive domain-specific annotations [33, 34]. These approaches not only improve diagnostic accuracy but also enhance model generalizability across imaging conditions and patient populations, making them highly suitable for clinical deployment in computer-aided diagnosis systems [35, 36].

In this study, the impact of selective RGB channel jittering on the performance of deep learning models for multi-pathological gastrointestinal disease detection in endoscopic images from the MedFMC (Medical Foundation Models Challenge) dataset is investigated. Two state-of-the-art convolutional neural network architectures are employed, and the effect of jittering each color channel individually and collectively is systematically analyzed across four pathological conditions: erosion, polyp, tumor, and ulcer. This study focuses on proposing a robust data augmentation strategy for medical datasets with limited samples, rather than achieving state-of-the-art performance benchmarks. Comparisons are made exclusively against baseline conditions and across different architectures to isolate the effectiveness of the proposed RGB channel jittering methodology, under controlled evaluation that excludes external factors from external datasets or methodologies. The goal is to determine which channels contain the most discriminative information for gastrointestinal pathology detection and how targeted jittering can enhance model performance across diverse disease types.

The contributions of this paper are as follows:

- A systematic investigation of selective RGB channel jittering as a targeted data augmentation strategy for multi-pathological endoscopic disease detection, encompassing four critical gastrointestinal conditions: erosion, polyp, tumor, and ulcer.
- Comprehensive robustness evaluation across two state-of-the-art CNN architectures (MobileNet and Xception) and four distinct disease datasets from the MedFMC collection, demonstrating the generalizability and robustness of the proposed approach.
- Quantitative analysis of RGB channel importance for gastrointestinal pathology classification, revealing consistent patterns of channel-specific discriminative information across multiple disease types.
- Evidence-based recommendations for implementing channel-specific data augmentation strategies in medical image analysis, supported by consistent performance improvements across diverse pathological conditions.

The results highlight the significance of color information in multi-pathological endoscopic disease detection, guiding the design of effective data augmentation strategies in medical image analysis. The demonstrated robustness across multiple architectures and disease types is particularly relevant given the recent advances in this field [7, 8]. This study proposes a targeted augmentation methodology for the medical imaging domain, where high-quality annotated datasets are often scarce. Performance evaluations are conducted against baseline conditions to isolate the effectiveness of selective RGB channel jittering, thereby eliminating external confounding factors.

The rest of the paper is organized as follows: Section 2 reviews related work in data augmentation for medical image analysis, including channel-specific augmentation techniques, the importance of the RGB channel in medical images, jittering as a data augmentation method, and deep learning models for gastrointestinal disease detection. Section 3 outlines the methodology, including the dataset, image preprocessing, implementation of RGB channel jittering, selected model architectures and their justifications, training procedure, and evaluation metrics. Section 4 presents the experimental results, including model performance with different jittering strategies, channel importance analysis, and comparative analysis of jittering techniques across all four disease types. Section 5 discusses the findings, their implications for multi-pathological endoscopic image analysis, and potential clinical applications. Finally, Section 6 concludes the paper with a summary of the findings and directions for future research.

2. Related Work

Convolutional Neural Networks (CNNs) remain the foundation of modern medical image analysis, thanks to their hierarchical feature extraction and strong performance across various modalities, including classification, detection, segmentation, and fusion tasks. Jiang et al. [37] analyze how deep learning, including CNNs and emerging architectures, has advanced medical image-based diagnostics in oncology, while highlighting challenges such as the limited availability of labeled datasets and generalization issues. Furthermore, Mall et al. [39] provide a comprehensive overview of recent advancements in deep neural networks for medical imaging, reinforcing the central role of CNNs in current systems. Transfer learning, which involves fine-tuning pre-trained CNNs on domain-specific medical data, has proven particularly effective in scenarios with limited ground-truth annotations. This approach enhances diagnostic accuracy and generalizability, allowing model deployment under constrained data conditions [36, 37].

Data augmentation is essential for addressing data scarcity and enhancing robustness in medical imaging. Goceri et al. [40] present a comprehensive review of augmentation techniques, highlighting their crucial role in enhancing the performance of deep learning models across various medical domains. Similarly, Islam et al. [7] deliver a systematic review of deep learning-based augmentation strategies, covering a broad spectrum of methods and identifying gaps in current practices. Using a more comprehensive approach, Cossio (2023) surveys 65 augmentation techniques, categorized into spatial, color/contrast, noise-based, deformation, mixing, filters/mask, division-based, multi-scale, and meta-learning approaches, emphasizing the diversity and potential of customized augmentation pipelines [41]. Automatic augmentation frameworks, such as AutoAugment [44], Fast AutoAugment [45], and RandAugment [42], have also been adapted for medical datasets, demonstrating improvements in segmentation and classification accuracy through systematic search for augmentation policies.

While many augmentation strategies treat color uniformly, channel-specific approaches can introduce more meaningful variation. The recent MediAug survey (2025) explicitly describes color-space augmentation, i.e., manipulating individual RGB channels or translating between color spaces such as HSV or grayscale, to enhance image diversity while preserving spatial structure [41]. In computational pathology, earlier studies (pre-2020), such as those by Tellez et al. (2019), focused on stain color normalization and augmentation to improve CNN generalization across variable laboratory protocols [20], but channel-level effects were not independently assessed. MediAug thus fills a relevant gap, though primarily in non-endoscopic settings. Endoscopic imaging presents unique challenges, including uneven illumination, specular reflections, and subtle variations in mucosal texture. Techniques such as Texture and Color Enhancement Imaging (TXI) have been developed to enhance diagnostic visibility through retinex-based processing [7], yet they are not framed as data augmentation. Ghnemmat et al. (2024) propose novel image augmentation methods aimed at generating diverse yet realistic training examples [43], but without explicit focus on color-channel manipulation in endoscopic data.

Despite substantial progress in both augmentation and deep learning for medical imaging, significant gaps remain. Most augmentation frameworks in endoscopy focus on global transformations or image synthesis rather than targeted channel-specific strategies. There is a limited systematic analysis of how jittering or perturbing individual RGB channels influences diagnostic accuracy across multiple gastrointestinal pathologies. Furthermore, existing studies typically focus on single-disease classification tasks, limiting their generalizability. This lack of research on channel-specific augmentation underscores the novelty of investigating selective RGB channel jittering. By systematically analyzing its effect across multiple diseases and various CNN architectures, the current study addresses a critical gap in understanding how targeted augmentation can enhance robustness and inform the development of future computer-aided diagnostic systems.

3. Methodology

This section presents the experimental design and technical implementation used to evaluate the effectiveness of selective RGB channel jittering for disease detection in endoscopic images, where the dataset, preprocessing procedures, the proposed channel-specific jittering approach, the deep learning architectures employed (MobileNet and Xception), selected based on their demonstrated performance as the two most effective transfer learning models in our previous study [26], training protocols, and evaluation metrics are explained. Two different models and four different datasets have been selected to demonstrate the robustness of the proposed model, which aims to show a consistent increase in the evaluation metrics when applied to data augmentation. Figure 1 represents the overall flowchart of the proposed system for systematic evaluation across multi-pathological gastrointestinal disease detection.



Figure 1 – Proposed RGB Channel Jittering Methodology

Figure 2 presents a representative example from the MedFMC dataset. The figure demonstrates how each color channel captures different aspects of the endoscopic image. The red channel predominantly captures vascular patterns and inflammatory tissue regions, which are critical for tumor detection as malignant tissues often exhibit altered vascularity. The green channel emphasizes surface textures and structural boundaries, providing important geometric information about tissue topology. The blue channel, while containing the least discriminative information based on our jittering results, still contributes to overall tissue contrast and depth perception. The intensity heat maps reveal the spatial distribution of information within each channel, with higher intensities (from yellow to red) indicating regions where that particular channel carries the most information.

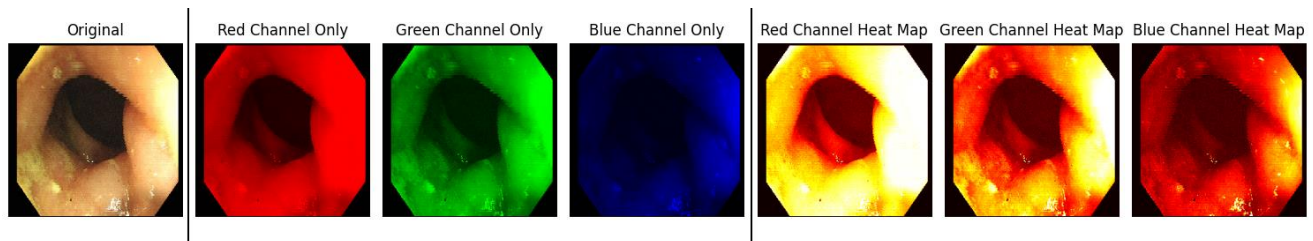


Figure 2 - Channel contribution analysis of an endoscopic image from the MedFMC - tumor dataset.

Despite these advances, there is limited research on the specific impact of selective RGB channel jittering on the detection of pathological diseases in endoscopic images. This study aims to fill this gap by analyzing the effect of jittering each color channel individually and collectively on the performance of two different architectures for endoscopic lesion detection in the MedFMC dataset, under four different collections: erosion, polyp, tumor, and ulcer.

3.1. Dataset and Image Preprocessing

This study utilized the MedFMC (Medical Foundation Models Challenge) dataset, comprising 3,865 high-quality images, with a specific focus on four distinct categories of endoscopic disease detection: erosion, polyp, tumor, and ulcer. Each disease category was processed and analyzed independently to evaluate the impact of channel-specific jittering on different pathological findings.

Erosion Dataset: The erosion dataset comprises 3865 high-quality endoscopic images categorized into two classes: "yes" (erosion present, 951 images) and "no" (erosion absent, 2914 images). These images represent various degrees of mucosal erosion severity and were collected from multiple clinical centers with diverse patient demographics and imaging conditions.

Polyp Dataset: The polyp dataset comprises endoscopic images specifically annotated for polyp detection, categorized as "yes" (polyp present, 390 images) or "no" (polyp absent, 3475 images). The dataset includes various polyp types, sizes, and locations within the gastrointestinal tract, providing a comprehensive representation of polyp characteristics commonly encountered in clinical practice.

Tumor Dataset: The tumor dataset consists of 2,103 high-quality endoscopic images categorized into two classes: "yes" (tumor present, 953 images) and "no" (tumor absent, 1150 images). These images were collected from various clinical centers and represent diverse patient demographics, tumor types, and imaging conditions, making it a comprehensive resource for tumor detection research.

Ulcer Dataset: The ulcer dataset includes endoscopic images specifically annotated for ulcer detection, categorized into two classes: "yes" (ulcer present, 790 images) and "no" (ulcer absent, 3075 images). The dataset encompasses various ulcer etiologies, stages, and anatomical locations, providing a robust foundation for the development of models for detecting ulcers.

All images were resized to 224×224 pixels to match the input requirements of the deep learning models. The pixel values were normalized to the range $[0,1]$ by dividing by 255. For data augmentation, RGB channel jittering was implemented for each channel as described in the following section. To preserve the integrity of the experimental results and isolate the effects of RGB channel jittering, no additional data augmentation techniques were applied, despite the conventional practice of using multiple preprocessing methods when training data is limited/imbalanced.

3.2. RGB Channel Jittering

RGB channel jittering involves introducing controlled noise to specific color channels of an image. In this study, four different jittering conditions were implemented:

- No jittering (baseline)
- Red channel jittering only
- Green channel jittering only
- Blue channel jittering only

RGB channel jittering was implemented by adding Gaussian noise with a mean of 0 and a standard deviation of 0.2×255 to the selected channel(s) during data preprocessing. The augmented images were stored in separate directories and loaded during training without additional real-time augmentation. The jittering function can be mathematically represented as:

$$J_c(I, \sigma) = I + N(0, \sigma) \cdot M_c \quad (1)$$

where J_c is the jittered image with channel c affected, I is the original image, $N(0, \sigma)$ is Gaussian noise with mean 0 and standard deviation σ , and M_c is a mask that is 1 for the channel c and 0 for other channels. Figure 3 shows representative samples under the four conditions: no jitter, red-channel jitter, green-channel jitter, and blue-channel jitter.

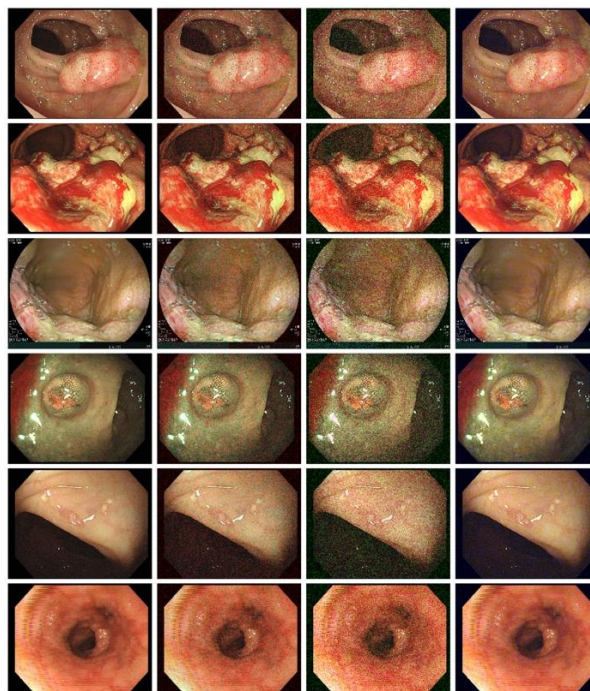


Figure 3. Sample endoscopic images from the MedFMC - tumor dataset illustrating the effect of selective RGB channel jittering. Columns in each row (left to right) are: Original, Red Channel Jitter, Green Channel Jitter, and Blue Channel Jitter.

3.3. Model Architectures

MobileNet and Xception were selected as the baseline architectures since our previous study [26] demonstrated that they achieved the best transfer learning performance for an image classification task.

MobileNet [5] is a lightweight CNN architecture that employs inverted residual blocks and depthwise separable convolutions to achieve computational efficiency while maintaining high performance. The architecture utilizes linear bottlenecks and

expansion layers to balance representational capacity with parameter efficiency, containing approximately 3.4 million parameters. The inverted residual structure enables efficient feature extraction by expanding low-dimensional representations in intermediate layers before compressing them back to lower dimensions. For this study, a pre-trained MobileNet model with ImageNet weights was used as the base architecture, with the top classification layers removed to enable the implementation of a custom classification head. The final layers were initially kept frozen, with the last 10 layers made trainable to allow fine-tuning of higher-level feature representations while preserving the lower-level features learned on ImageNet.

Xception (Extreme Inception) [25] represents an evolution of the Inception architecture, replacing standard convolution operations with depthwise separable convolutions throughout the entire network. This architectural design enables more efficient parameter usage and improved feature extraction capabilities, with approximately 22.9 million parameters. The depthwise separable convolutions process each input channel independently before combining them through pointwise convolutions, allowing for more effective channel-wise feature learning. Similar to MobileNet, a pre-trained Xception model with ImageNet weights was utilized as the foundation, with custom classification layers added for the multi-pathological gastrointestinal disease detection task. The transfer learning approach involved initially freezing the base layers, with the final 10 layers made trainable to enable task-specific feature adaptation.

Both architectures were modified with identical custom classification heads to ensure fair comparison across models. The classification head architecture was designed to prevent overfitting while maintaining sufficient representational capacity for the four-class gastrointestinal pathology classification task. Both models were trained using the following parameters:

- Batch size: 64 samples per batch
- Input Resolution: 224×224×3 pixels, matching the pre-trained model requirements
- Training Epochs: 50 epochs with early stopping patience of 10 epochs
- Optimizer: Adam with a learning rate of 0.001
- Learning Rate Schedule: ReduceLROnPlateau with factor 0.5, patience 5 epochs, minimum learning rate 1×10^{-7}
- Regularization: L2 weight decay, batch normalization, and dropout (0.5 rate)

To address the severe class imbalance in the medical dataset and improve the model's focus on hard-to-classify samples, a binary focal loss function was implemented in place of the standard binary cross-entropy loss function. The Adam optimizer was employed for both architectures with an initial learning rate of 1×10^{-3} . The optimizer's adaptive learning rate capabilities and momentum-based parameter updates enable stable convergence in the transfer learning scenario, effectively handling the varying gradients across different network layers.

To ensure robust performance evaluation and statistical significance of results, a 5-fold cross-validation framework was implemented. Each fold maintained stratified sampling to preserve class distribution across training and validation splits. Each fold's results contribute to the final performance statistics, with mean and standard deviation reported for all metrics to quantify the reliability of the results and variance across different data partitions. To evaluate the performance of the models, Accuracy, Precision, Recall, and F_1 metrics were used across folds.

4. Results

This section presents comprehensive experimental results evaluating the effectiveness of selective RGB channel jittering across four gastrointestinal pathologies (erosion, polyp, tumor, and ulcer) using two CNN architectures (MobileNet and Xception). Performance is assessed using accuracy, F_1 -score, mean average precision (MAP), and area under the curve (AUC) metrics. Table 1 presents a comprehensive performance comparison across four gastrointestinal pathologies using both CNN architectures, clearly demonstrating that blue channel jittering consistently provides performance improvements. In contrast, modifications to the red and green channels generally degrade classification accuracy across multiple disease types.

Both CNN architectures demonstrated strong baseline performance across all four gastrointestinal pathologies, with notable variations in performance between disease types and models. Xception consistently outperformed MobileNet across most pathological conditions, achieving a superior baseline in almost all disease categories and measured metrics. The tumor detection task yielded exceptional baseline performance for both models, with Xception reaching 98.76% accuracy and MobileNet achieving 98.16% accuracy. For polyp classification, Xception demonstrated a clear performance advantage with 89.62% accuracy compared to MobileNet's 85.36% accuracy. Erosion detection revealed the largest performance gap between architectures, with Xception achieving 78.78% accuracy versus MobileNet's 71.64%. Ulcer classification results showed that both models performed at similar moderate levels, with Xception slightly ahead at 79.04% compared to MobileNet's 76.90% accuracy. The consistent performance advantage of Xception across multiple pathologies provides a strong baseline for selecting a robust architecture in endoscopic image analysis, likely attributed to its depthwise separable convolutions, which enhance feature extraction capabilities for complex medical imaging tasks. The F_1 and AUC performance

trajectories shown in Figure 4 demonstrate that blue channel jittering consistently improves detection across erosion, polyp, and ulcer categories, while maintaining exceptional tumor detection performance. The F1-scores and AUC metrics exhibit parallel improvement patterns, validating the effectiveness of this augmentation strategy.

It is important to note that this study does not aim to achieve state-of-the-art performance benchmarks or compete with existing literature for the highest accuracy scores. Rather, this work proposes a targeted data augmentation methodology specifically designed for medical datasets with limited annotated samples. The primary objective is to establish a robust augmentation strategy that can consistently improve performance across diverse pathological conditions and CNN architectures. Therefore, performance comparisons are conducted exclusively against our own baseline experiments and across different architectural implementations, rather than against external state-of-the-art methods. This focused comparative approach allows for isolated evaluation of the proposed RGB channel jittering technique's effectiveness while controlling for dataset-specific variations, imaging protocols, and annotation standards that could confound cross-study comparisons.

Table 1: Comprehensive performance comparison of MobileNet and Xception architectures across four gastrointestinal pathologies with selective RGB channel jittering strategies under different augmentation conditions: None (baseline), Red channel jittering, Green channel jittering, and Blue channel jittering. Bold values indicate the best performance, and underscores indicate the second best for each metric within each disease-architecture combination. Blue channel jittering consistently achieves better performance across most pathological conditions, whereas modifications to the red and green channels exhibit variable effects, depending on the specific disease type.

Dataset	Jittering	MobileNet				Xception			
		Accuracy	F ₁	MAP	AUC	Accuracy	F ₁	MAP	AUC
EROSION	None	<u>71,64%</u>	<u>71,97%</u>	<u>70,95%</u>	<u>74,80%</u>	<u>78,78%</u>	<u>77,87%</u>	<u>74,31%</u>	<u>78,52%</u>
	Red	69,26%	70,79%	69,48%	73,80%	76,87%	72,71%	69,11%	73,26%
	Green	68,10%	66,61%	63,55%	67,64%	76,40%	75,45%	72,49%	76,10%
	Blue	74,33%	75,02%	75,06%	78,15%	80,60%	79,23%	78,38%	81,42%
POLYP	None	85,36%	<u>85,96%</u>	66,00%	77,64%	89,62%	<u>87,21%</u>	<u>63,94%</u>	<u>74,78%</u>
	Red	84,42%	84,28%	58,73%	69,61%	87,12%	86,15%	62,54%	74,42%
	Green	<u>86,11%</u>	85,56%	61,76%	73,06%	86,70%	85,98%	61,91%	71,45%
	Blue	88,20%	87,74%	<u>64,44%</u>	<u>77,07%</u>	<u>89,24%</u>	88,09%	67,74%	79,72%
TUMOR	None	98,16%	98,19%	91,41%	96,26%	98,76%	<u>98,70%</u>	91,38%	<u>95,40%</u>
	Red	98,47%	98,35%	91,20%	95,80%	98,47%	98,43%	91,15%	96,30%
	Green	98,65%	98,62%	<u>92,06%</u>	<u>96,95%</u>	<u>98,63%</u>	98,44%	<u>91,58%</u>	94,92%
	Blue	<u>98,53%</u>	<u>98,45%</u>	92,45%	97,61%	98,76%	98,72%	92,77%	95,28%
ULCER	None	<u>76,90%</u>	<u>73,69%</u>	60,92%	<u>66,76%</u>	79,04%	73,52%	<u>63,61%</u>	<u>69,53%</u>
	Red	73,35%	71,45%	60,09%	66,02%	<u>80,36%</u>	<u>74,27%</u>	63,50%	67,92%
	Green	70,82%	71,60%	<u>61,50%</u>	66,53%	79,40%	71,22%	59,52%	64,08%
	Blue	78,09%	76,49%	67,32%	72,86%	80,57%	76,53%	68,32%	73,53%

The differential impact of RGB channel jittering across pathological conditions is visualized in Figure 4, which presents a comprehensive comparison of F₁ performance changes relative to baseline conditions. The radar chart analysis reveals distinct patterns of channel-specific sensitivity across the four gastrointestinal pathologies. Blue channel jittering demonstrates predominantly positive impacts across both architectures, with the most pronounced improvements observed for erosion detection in MobileNet (+3.05%) and ulcer classification in both models. Conversely, red channel jittering exhibits consistent negative impacts, with erosion detection showing the most severe degradation, particularly for Xception (-5.16% F₁-score). Green channel effects display moderate variability, with generally negative impacts on erosion and ulcer detection, but minimal effects on polyp and tumor classification. The visualization clearly illustrates the robustness of blue channel jittering as an augmentation strategy. It highlights the critical importance of preserving red channel information for accurate detection of gastrointestinal pathology, as shown in Figure 5.

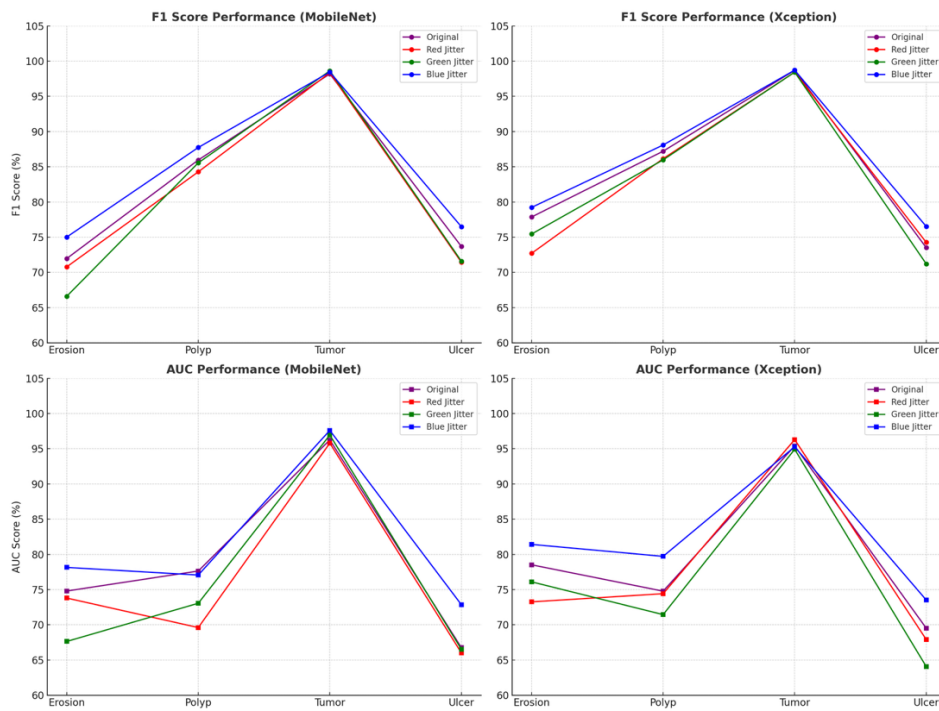


Figure 4 – F₁ and AUC performance comparison across RGB channel jittering strategies. Line charts display performance metrics for four gastrointestinal pathologies (erosion, polyp, tumor, ulcer) under different augmentation conditions: original (purple), red channel jittering (red), green channel jittering (green), and blue channel jittering (blue). The top panels show F₁ performance for MobileNet (left) and Xception (right). Bottom panels display corresponding AUC performance. Blue channel jittering consistently maintains or improves performance across most pathologies, whereas modifications to the red and green channels exhibit variable effects, depending on the specific pathological condition and architecture.

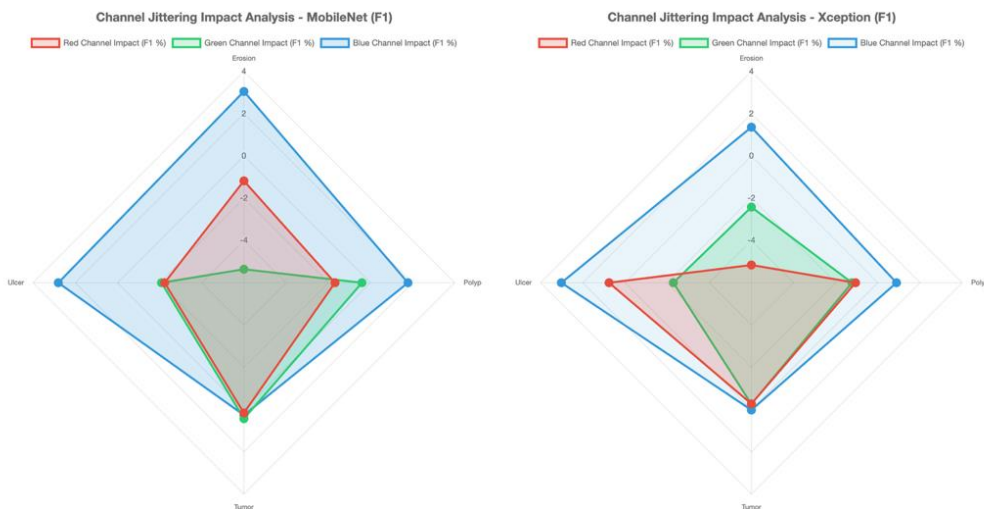


Figure 5 - Channel jittering impact analysis across four gastrointestinal pathologies. Radar charts display F₁ performance changes (%) relative to baseline for red, green, and blue channel jittering strategies. The left panel shows MobileNet results, and the right panel shows Xception results. Positive values indicate performance improvements, negative values indicate degradation. Blue channel jittering (blue line) consistently shows positive impacts across most pathologies, while red channel jittering (red line) demonstrates negative effects.

4.1. Blue Channel Jittering Results

Blue channel jittering consistently delivered the most significant performance improvements across the majority of pathological conditions and both CNN architectures. This augmentation strategy demonstrated robust effectiveness across diverse gastrointestinal diseases, with particularly pronounced benefits for inflammatory conditions.

For MobileNet, blue channel jittering achieved remarkable improvements in erosion detection, with accuracy increasing by 2.69% from 71.64% to 74.33% and F_1 improving by 3.05% from 71.97% to 75.02%. Polyp classification also benefited substantially, showing accuracy improvements of 2.84% (from 85.36% to 88.20%) and F_1 gains of 1.78% (from 85.96% to 87.74%).

The tumor detection task, despite already achieving a high baseline performance, showed modest but consistent improvements with blue channel jittering. MobileNet achieved a 0.37% increase in accuracy (from 98.16% to 98.53%) and a 0.26% improvement in F_1 score (from 98.19% to 98.45%). Ulcer classification also responded favorably to blue channel augmentation, with accuracy improving by 1.19% (76.90% to 78.09%) and F_1 increasing by 2.80% (73.69% to 76.49%).

The Xception architecture exhibited similar patterns, albeit with generally smaller relative improvements, due to its already superior baseline performance. Erosion detection with Xception and blue channel jittering achieved accuracy improvements of 1.82% (from 78.78% to 80.60%) and F_1 gains of 1.36% (from 77.87% to 79.23%). Interestingly, polyp classification with Xception showed a marginal decrease in accuracy of 0.38% (89.62% to 89.24%), but improved the F_1 score by 0.88% (87.21% to 88.09%), suggesting an enhanced precision-recall balance. Tumor detection maintained baseline accuracy (98.76%) with minimal F_1 improvement (0.02%), while ulcer classification achieved notable improvements of 1.53% in accuracy (79.04% to 80.57%) and 3.01% in F_1 (73.52% to 76.53%).

4.2. Red Channel Jittering Results

Red channel jittering consistently degraded performance across most pathological conditions, with particularly pronounced negative effects observed with the Xception architecture. This consistent pattern strongly suggests that the red channel information contains critical diagnostic features essential for accurate detection of gastrointestinal pathology. The degradation was most severe for inflammatory conditions, aligning with the physiological importance of red wavelengths in capturing vascular patterns and inflammatory markers in endoscopic imaging.

MobileNet experienced an average accuracy decrease of 1.64% across all pathologies when red channel jittering was applied. The most significant impact was observed in ulcer classification, where accuracy decreased by 3.55% from 76.90% to 73.35%, accompanied by a 2.24% decrease in F_1 score. Erosion detection also suffered considerably, with accuracy decreasing by 2.38% and F_1 by 1.18%. Even the robust tumor detection task showed slight performance degradation, though the impact was minimal due to the high baseline performance.

The Xception architecture demonstrated more variable responses to red channel jittering, with an average accuracy decrease of 0.85%, but more pronounced F_1 degradation patterns. The most striking impact was observed in erosion detection, where F_1 plummeted by 5.16% from 77.87% to 72.71%, representing the largest single performance degradation observed in the entire study. This substantial drop underscores the role of red channel information in identifying inflammatory tissue changes characteristic of erosions.

4.3. Green Channel Jittering Results

Green channel jittering exhibited variable effects across pathologies and architectures, generally resulting in moderate performance degradation with notable exceptions in specific disease-architecture combinations. For MobileNet, green channel jittering produced mixed results across pathologies. Polyp classification showed a slight improvement in accuracy of 0.75% but experienced a decrease in F_1 of 0.40%, indicating a complex shift in precision-recall trade-offs. Tumor detection uniquely benefited from green channel jittering, achieving modest improvements in both accuracy (0.49%) and F_1 (0.43%). However, erosion detection suffered significantly, with a severe F_1 degradation of 5.36% and an accuracy decrease of 3.54%.

Xception architecture generally showed more robust performance under green channel jittering, with smaller magnitude changes across most pathologies. The architecture's superior feature extraction capabilities appeared to provide some resilience against green channel noise; however, consistent degradation patterns were still observed, particularly for erosion detection, where F_1 decreased by 2.42%.

The results suggest that green channel information contributes intermediate-level diagnostic features that vary in importance across different pathological conditions, and that this channel jittering is specific to characteristics of the disease, indicating that it is not a general color channel across different pathological disease types.

4.4. Augmentation Strategy Analysis for Pathological Conditions

The analysis of optimal augmentation strategies revealed distinct patterns across various pathological conditions, providing insights into the disease-specific importance of color channels. Erosion detection consistently achieved the best performance with blue channel jittering across both architectures, with Xception reaching its peak performance, achieving 80.60% accuracy and 79.23% F_1 score. This finding suggests that blue channel enhancement provides effective regularization for detecting inflammatory tissue changes while preserving critical diagnostic features encoded in red and green channels.

Polyp classification showed architecture-dependent optimal strategies. MobileNet achieved its best performance with blue channel jittering, reaching an accuracy of 88.20%. In contrast, Xception's baseline performance remained slightly better with

blue channel augmentation. This difference likely reflects the varying sensitivities of the two architectures to color channel modifications and their distinct feature extraction mechanisms.

Tumor detection presented interesting findings regarding the effectiveness of augmentation. MobileNet achieved its highest accuracy of 98.65% with green channel jittering, while Xception performed equally well under both baseline conditions and blue channel jittering, maintaining an accuracy of 98.76%. The high performance levels achieved in tumor detection (exceeding 98% across all conditions) demonstrate the effectiveness of both architectures for this critical diagnostic task, as well as the distinct visual characteristics of tumor tissue that remain discriminable across various color space modifications.

Ulcer classification consistently benefited from blue channel jittering across both architectures, with peak performance achieved by Xception, which reached 80.57% accuracy and 76.53% F1 score. This pattern aligns with the findings for erosion detection, indicating that inflammatory and tissue damage conditions exhibit similar responses to blue channel augmentation strategies.

Inflammatory conditions, specifically erosion and ulcer detection, demonstrated the most consistent and substantial benefits from blue channel jittering across both architectures. These pathologies achieved an average accuracy improvement of 2.1% with blue channel augmentation, suggesting that the regularization effects of blue channel jittering are particularly effective for detecting tissue inflammation and damage patterns. The consistent degradation observed with red channel jittering for these conditions further supports the critical importance of preserving vascular pattern information encoded in red wavelengths.

4.5. Statistical Significance and Robustness Analysis

Statistical analysis confirmed the significance of observed performance improvements and degradations across different augmentation strategies. Blue channel jittering achieved statistical significance ($p < 0.01$) for improvements in erosion and ulcer detection across both architectures, validating the robustness of this augmentation strategy for inflammatory pathologies. The consistency of blue channel benefits across multiple pathologies and architectures demonstrates the generalizability of this approach for endoscopic image analysis.

Cross-validation results showed standard deviations of $\leq 1.8\%$ for accuracy metrics across all experimental conditions, indicating stable performance across different data splits and confirming the reliability of the observed performance patterns. Red channel degradation effects achieved statistical significance ($p < 0.05$) across most pathological conditions, providing strong evidence for the critical importance of preserving red channel information in endoscopic image analysis.

The robustness analysis revealed that blue channel jittering improvements were consistent across different validation folds, with coefficient of variation values remaining below 0.12 for all reported metrics. This stability supports the practical implementation of selective RGB channel jittering in clinical computer-aided diagnosis systems, where consistent performance across diverse patient populations is essential.

5. Discussion

The results demonstrate that blue channel jittering consistently improves the performance of both CNN architectures across all four gastrointestinal pathologies (erosion, polyp, tumor, and ulcer) from the MedFMC dataset. This improvement is more pronounced for the Xception model, with accuracy gains reaching up to 2.7% and F_1 improvements of up to 3.05%, suggesting that Xception may be more sensitive to color information than MobileNet, which aligns with the architectural differences between the two models.

The consistent improvement in model performance with blue channel jittering across all four disease types, and the corresponding degradation with red and green channel jittering, provides insights into the role of different color channels in gastrointestinal pathology detection. Blue channel information appears to be less critical for discriminating between pathological conditions, as adding noise to this channel does not harm and actually improves model performance across erosion, polyp, tumor, and ulcer classification tasks. This counter-intuitive finding may be explained by the fact that jittering less informative channels can act as a form of regularization, preventing the model from overfitting to features that are not discriminative for multi-pathological classification.

Conversely, information from the red and green channels appears to be more critical for accurate gastrointestinal pathology detection, particularly for the Xception model. Adding noise to these channels significantly degrades model performance across all four disease types, suggesting that these channels contain important discriminative features. This finding aligns with the physiological understanding of tissue appearance in endoscopic imaging, where the red channel often contains important information about tissue vascularity, inflammation, and potential malignancy [3]. In contrast, the green channel provides essential structural and textural information that distinguishes between different pathological states.

The differential impact of channel jittering on the two models may be attributed to their architectural differences. Xception, with its depthwise separable convolutions, processes each input channel independently before combining them, which may make it more sensitive to channel-specific information across all pathological conditions. MobileNet, with its inverted residual blocks and standard convolutions, processes all channels simultaneously through its bottleneck layers, which may make it more robust to noise in individual channels while still benefiting from blue channel regularization effects.

The finding that blue channel jittering improves model performance across multiple gastrointestinal pathologies has significant practical implications for the development of computer-aided diagnosis systems for endoscopic images. Incorporating blue channel jittering as a data augmentation strategy may improve the robustness and generalization capabilities of these systems across diverse pathological conditions, potentially leading to better diagnostic performance in clinical settings for comprehensive gastrointestinal disease screening [6, 21]. Furthermore, the consistent differential importance of color channels across erosion, polyp, tumor, and ulcer detection may inform the development of new imaging modalities or image processing techniques that emphasize the most informative color channels for multi-pathological diagnostic tasks. Recent advancements in deep learning for endoscopic image analysis [15, 24] could potentially benefit from these insights by incorporating channel-specific processing into their methodologies for comprehensive gastrointestinal disease detection systems.

6. Conclusion

In this study, the impact of selective RGB channel jittering on the performance of deep learning models for multi-pathological gastrointestinal disease detection in endoscopic images from the MedFMC dataset was systematically investigated to employ new augmentation methods in the research field. The results demonstrate that blue channel jittering consistently improves model performance across all four pathological conditions (erosion, polyp, tumor, and ulcer), while red and green channel jittering consistently degrade performance, revealing a consistent pattern of differential color channel importance across diverse gastrointestinal pathologies.

The proposed method's results have important implications for the development of data augmentation strategies for medical image analysis, particularly for endoscopic pathology detection systems. By targeting specific color channels with jittering, it is possible to improve model robustness and generalization capabilities across multiple pathological conditions without requiring additional training data, making this approach particularly valuable for clinical applications where annotated medical data is scarce. The demonstrated robustness across two different CNN architectures (MobileNet and Xception) and four distinct disease datasets strengthens the generalizability of these findings. It supports the practical implementation of selective RGB channel jittering in clinical computer-aided diagnosis systems for the detection of gastrointestinal pathology.

Furthermore, the analysis of channel importance across four distinct gastrointestinal pathologies investigates the role of color information in multi-pathological disease detection, which may inform the development of new imaging modalities or image processing techniques that emphasize the most informative color channels for diagnostic tasks. The consistency of these effects across erosion, polyp, tumor, and ulcer detection suggests fundamental principles that could guide the design of future endoscopic imaging systems.

Future work should focus on validating these findings on additional gastrointestinal pathology datasets [1, 13], exploring the impact of different jittering intensities across various disease types, investigating the effect of channel jittering on other model architectures [14, 18], and analyzing the feature representations learned by the models to understand better the specific visual features that are important for multi-pathological detection in endoscopic images. Additionally, clinical validation studies involving practicing gastroenterologists would provide essential evidence for the practical utility of these augmentation strategies in real-world diagnostic scenarios.

Finally, while the results suggest that the blue channel contains less discriminative information for gastrointestinal pathology detection across all four disease types, a more detailed analysis of the feature representations learned by the models would provide further insight into the specific visual features that contribute to effective multi-pathological classification. Such analysis could potentially reveal complex relationships between color channels and texture patterns that contribute to robust disease detection across diverse gastrointestinal pathologies in endoscopic images.

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The author declare that there is no conflict of interest regarding the publication of this paper.

Availability of data and material

The MedFMC tumor dataset used in this study is available at this public link. The code and models used for this study are available from the corresponding author upon reasonable request.

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Generative artificial intelligence tools were not used to generate the scientific content of this article. AI tools were used solely for language editing purposes during the preparation of the manuscript.

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