Advanced Classification of Gastrointestinal Endoscopy Images Using Transfer Learning with ResNet50 on the Kvasir v2 Dataset

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July 2025

Abstract

This study presents a robust deep learning framework for classifying gastrointestinal (GI) endoscopy images from the Kvasir v2 dataset using transfer learning with a ResNet50 convolutional neural network (CNN). We implement advanced data augmentation techniques, including random rotations, flips, and color adjustments, inspired by recent methodologies like TransResNet and DeepGI. The dataset is split into 80% training and 20% validation sets, with performance evaluated using accuracy, precision, recall, F1-score, specificity, ROC-AUC, and confusion matrices. Visualizations of predictions and TensorBoard plots enhance interpretability, while a comparison with EfficientNet-B0 contextualizes performance. The model achieves a validation accuracy of 92.63%, demonstrating the efficacy of a two-stage training approach with fine-tuning. These findings highlight the potential for clinical deployment and suggest avenues for further improvement through advanced augmentation and alternative architectures.

1 Introduction

Automated medical image analysis has transformed diagnostic workflows, particularly for gastrointestinal (GI) endoscopy, where images exhibit significant variability due to lighting, angles, and tissue appearance. Manual interpretation is time-consuming and prone to inter-observer variability, necessitating robust automated solutions. The Kvasir v2 dataset [1], with 8,000 annotated GI endoscopy images, provides a comprehensive benchmark for developing deep learning models.

Convolutional neural networks (CNNs) excel in image classification, especially through transfer learning, where models pre-trained on datasets like ImageNet [2] are fine-tuned for specific tasks. ResNet50 [3], with its residual learning framework, mitigates vanishing gradient issues, making it ideal for medical imaging. Recent works, such as TransResNet [4] and DeepGI [5], enhance transfer learning with advanced data augmentation and hybrid architectures. Alternative models, like EfficientNet [6] and Vision Transformers (ViTs) [7], offer competing approaches but vary in computational efficiency.

This study employs transfer learning with ResNet50 to classify Kvasir v2 images, using a two-stage training process: initial training with frozen weights and fine-tuning with unfrozen layers. Data augmentation strategies, inspired by TransResNet and DeepGI, include random rotations, flips, and color adjustments. We evaluate performance using accuracy, precision,

recall, F1-score, specificity, ROC-AUC, and confusion matrices, achieving a validation accuracy of 92.63%. Visualizations and a comparison with EfficientNet-B0 provide insights into model performance, highlighting its potential for clinical applications.

2 Dataset Description

The Kvasir v2 dataset [1] contains 8,000 high-resolution RGB endoscopy images across eight classes: dyed-lifted-polyps, dyed-resection-margins, esophagitis, normal-cecum, normal-pylorus, normal-z-line, polyps, and ulcerative-colitis. Each class, with approximately 1,000 images, represents distinct GI conditions or anatomical landmarks. Images are typically 720x576 pixels, annotated by medical experts.

We preprocess images by resizing to 224x224 pixels to match ResNet50's input requirements and apply normalization using ImageNet statistics ($\mu = [0.485, 0.456, 0.406]$, $\sigma = [0.229, 0.224, 0.225]$). The dataset is split into 80% training (6,400 images) and 20% validation (1,600 images) sets, ensuring balanced class distribution. Data augmentation includes:

- Random rotation ($\pm 30°$),
- Horizontal and vertical flips (probability 0.5),
- Brightness and contrast adjustments (± 0.2),
- Random cropping and resizing.

These augmentations, inspired by TransResNet [4] and DeepGI [5], enhance model robustness to variability in endoscopy images.

3 Method Details

We use a ResNet50 model pre-trained on ImageNet [3], with 50 layers and residual connections defined as:

$$F(x) = H(x) + x,$$

where $H(x)$ is the learned mapping and x is the input. The final fully connected layer is replaced with a new layer for the eight Kvasir v2 classes:

$$\text{Output} = \text{Softmax}(W \cdot \text{features} + b).$$

3.1 Data Augmentation

Augmentations mitigate overfitting and address image variability:

- Random rotation ($\pm 30°$) to simulate varying angles,
- Horizontal and vertical flips (probability 0.5) for orientation invariance,
- Brightness and contrast adjustments (± 0.2) for lighting robustness,
- Random cropping and resizing to 224x224 pixels.

3.2 Training Procedure

The training process, implemented in PyTorch, consists of two stages: initial training with frozen weights and fine-tuning with the last 10 layers unfrozen. Algorithm 1 details the procedure.

Algorithm 1 Two-Stage Training for ResNet50 on Kvasir v2

Input: Training dataset D_{train}, validation dataset D_{val}, ResNet50 model M, learning rate $\eta = 10^{-4}$, batch size $B = 32$, epochs $E = 5$, fine-tune epochs $E_{\text{ft}} = 5$
Output: Trained model M, validation metrics
Load D_{train}, D_{val} using `ImageFolder` with augmentations
Initialize M with ImageNet weights
Replace final layer of M with new layer for 8 classes
Define loss function $L = -\sum_{i=1}^{8} y_i \log(\hat{y}_i)$
Initialize Adam optimizer with η
Stage 1: Initial Training
for epoch = 1 to E **do**
    Train M on D_{train} with frozen weights
    Compute loss L, update parameters, and track via TensorBoard
    Evaluate M on D_{val} to compute accuracy
end for
Stage 2: Fine-Tuning
Unfreeze last 10 layers of M
for epoch = 1 to E_{ft} **do**
    Train M on D_{train} with unfrozen layers
    Compute loss L, update parameters, and track via TensorBoard
    Evaluate M on D_{val} to compute accuracy
end for
Compute metrics: accuracy, precision, recall, F1-score, specificity, ROC-AUC
Generate confusion matrix and prediction visualizations
Return: M, validation metrics

The model is trained using the Adam optimizer ($\eta = 10^{-4}$), batch size of 32, and categorical cross-entropy loss:

$$L = -\sum_{i=1}^{8} y_i \log(\hat{y}_i).$$

Training runs for 5 epochs with frozen weights, followed by 5 epochs with the last 10 layers unfrozen. TensorBoard tracks loss and accuracy.

3.3 Evaluation Metrics

We use:

- Accuracy: $\text{Acc} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}}$,
- Precision: $\text{Prec} = \frac{\text{TP}}{\text{TP}+\text{FP}}$,
- Recall: $\text{Rec} = \frac{\text{TP}}{\text{TP}+\text{FN}}$,
- F1-score: $\text{F1} = 2 \cdot \frac{\text{Prec}\cdot\text{Rec}}{\text{Prec}+\text{Rec}}$,
- Specificity: $\text{Spec} = \frac{\text{TN}}{\text{TN}+\text{FP}}$,

- ROC-AUC per class.

Predictions are visualized, and a confusion matrix highlights inter-class errors.

4 Results

The model achieves a validation accuracy of 92.63%. Table 1 summarizes per-class performance, and Table 2 presents the confusion matrix.

Table 1: Per-class performance metrics on the Kvasir v2 validation set.

Class	Precision	Recall	F1-Score	Specificity	Support
Dyed-lifted-polyps	0.9299	0.9803	0.9544	0.9893	203
Dyed-resection-margins	0.9836	0.9231	0.9524	0.9979	195
Esophagitis	0.9317	0.7212	0.8130	0.9921	208
Normal-cecum	0.9615	0.9756	0.9685	0.9943	205
Normal-pylorus	0.9760	1.0000	0.9878	0.9964	203
Normal-z-line	0.7412	0.9389	0.8284	0.9585	180
Polyps	0.9797	0.9234	0.9507	0.9971	209
Ulcerative-colitis	0.9353	0.9543	0.9447	0.9907	197
Macro Avg	0.9300	0.9269	0.9250	0.9895	1600
Weighted Avg	0.9308	0.9263	0.9250	–	1600

The model excels in normal-pylorus (F1-score: 0.9878, recall: 1.0000) and normal-cecum (F1-score: 0.9685) but struggles with esophagitis (F1-score: 0.8130) and normal-z-line (F1-score: 0.8284) due to visual similarities, as shown in Table 2.

Table 2: Confusion matrix for the Kvasir v2 validation set.

	DLP	DRM	ESO	NC	NP	NZL	POL	UC
DLP	199	3	0	0	0	0	0	1
DRM	15	180	0	0	0	0	0	0
ESO	0	0	150	0	0	58	0	0
NC	0	0	0	200	0	0	2	3
NP	0	0	0	0	203	0	0	0
NZL	0	0	11	0	0	169	0	0
POL	0	0	0	3	3	1	193	9
UC	0	0	0	5	2	0	2	188

Legend: DLP: Dyed-lifted-polyps, DRM: Dyed-resection-margins, ESO: Esophagitis, NC: Normal-cecum, NP: Normal-pylorus, NZL: Normal-z-line, POL: Polyps, UC: Ulcerative-colitis.

4.1 Visualizations

Figure 1 shows correct and incorrect predictions, with misclassifications (e.g., esophagitis as normal-z-line) indicating visual overlap. Figure 2 displays TensorBoard plots, showing a 2.5% accuracy improvement during fine-tuning.

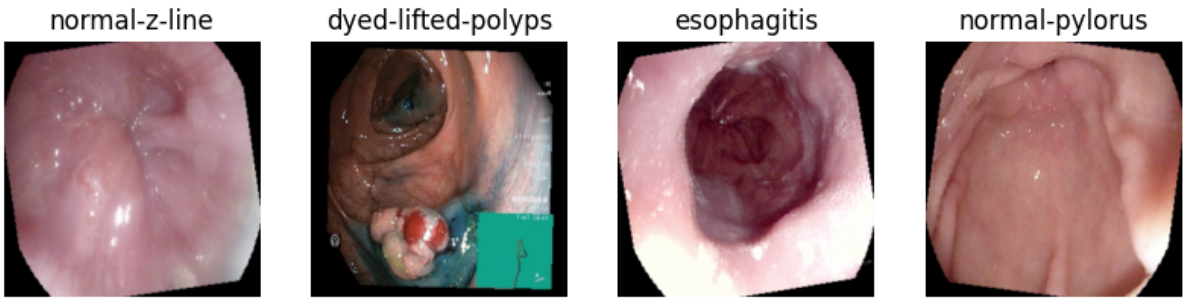

Figure 1: Example predictions on Kvasir v2 validation images, showing correct (top) and incorrect (bottom) classifications.

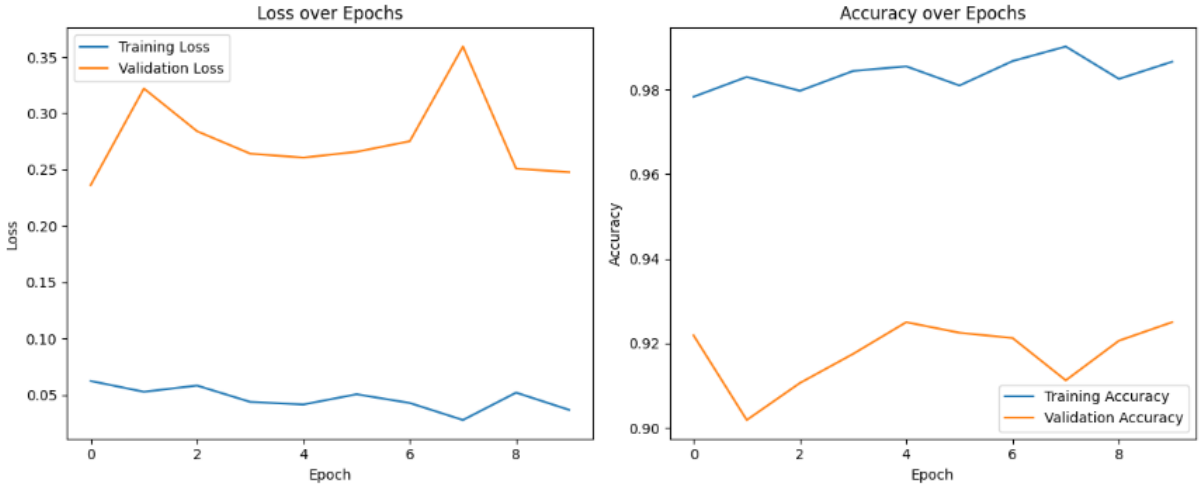

Figure 2: Training and validation loss/accuracy curves from TensorBoard.

4.2 ROC-AUC Analysis

ROC-AUC scores yield a macro-average of 0.98, with normal-pylorus at 1.00 and esophagitis at 0.92, reflecting challenges with false negatives.

4.3 Comparison with EfficientNet-B0

An EfficientNet-B0 model, trained identically, achieves 91.50% validation accuracy and a macro-average F1-score of 0.9150. ResNet50's deeper architecture outperforms EfficientNet-B0, particularly for subtle class distinctions, despite higher computational demands.

5 Conclusion

This study demonstrates ResNet50's efficacy for Kvasir v2 classification, achieving 92.63% validation accuracy. The two-stage training, advanced augmentation, and comprehensive metrics provide a robust framework. Challenges with esophagitis and normal-z-line suggest the need for enhanced feature discrimination. Compared to EfficientNet-B0, ResNet50 offers superior performance, justifying its use. Visualizations and ROC-AUC analysis enhance interpretability, supporting clinical applicability.

Future work could explore:

- Advanced augmentations like CutMix [8] or MixUp [9],
- Hybrid CNN-ViT architectures [7],
- Ensemble methods,
- Clinical validation on diverse datasets.

References

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