Automatic Classification of Gastrointestinal Diseases from Endoscopic Images Using Progressive Transfer Learning with EfficientNet-B4

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ABSTRACT

Gastric cancer and associated pathologies represent a major public health concern worldwide. The interpretation of endoscopic images, while essential for diagnosis, remains a complex task subject to significant inter-observer variability. This thesis addresses the automatic classification of gastrointestinal pathologies from endoscopic images using deep learning and transfer learning techniques.
A detailed review of classical and deep learning-based approaches was conducted, followed by a rigorous presentation of the theoretical foundations of convolutional neural networks. Based on this analysis, an EfficientNet-B4 architecture pre-trained on ImageNet was fine-tuned using a progressive two-phase strategy on the Kvasir-v2 benchmark dataset.
Targeted preprocessing techniques, data augmentation, class imbalance handling, and mixed precision training were integrated to improve the robustness and generalization of the model.

The results obtained demonstrate that a progressive fine-tuning strategy combined with adapted data augmentation achieves high classification performance and strong generalization ability, significantly outperforming previously published results on the same dataset. This work thus contributes to the development of reliable and interpretable computer-aided diagnosis systems, capable of assisting clinicians in the early detection of gastric lesions.

Keywords: Gastrointestinal Diseases, Endoscopic Images, Deep Learning, EfficientNet-B4, Transfer Learning, Medical Image Classification, Computer-Aided Diagnosis.

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INTRODUCTION

Gastrointestinal (GI) diseases constitute a significant global health burden, affecting millions of individuals annually and contributing substantially to morbidity and mortality worldwide [1]. Early and accurate diagnosis is essential for improving treatment outcomes, reducing healthcare costs, and increasing patient survival rates. Endoscopy remains the gold standard for diagnosing gastrointestinal disorders because it enables direct visualization of the digestive tract and facilitates the identification of lesions, polyps, ulcers, bleeding, and malignant tumors. However, the interpretation of endoscopic images is a complex and time-consuming task that depends heavily on the experience of gastroenterologists and is subject to inter-observer variability [2].

Recent advances in Artificial Intelligence (AI), particularly Deep Learning (DL), have transformed the field of medical image analysis by enabling automated feature extraction and high-accuracy image classification. Unlike conventional machine learning methods that rely on handcrafted features, deep learning models automatically learn hierarchical and discriminative representations directly from raw image data. Among these models, Convolutional Neural

Networks (CNNs) have demonstrated remarkable performance in numerous medical imaging applications, including disease detection, lesion segmentation, and computer-aided diagnosis (CAD) [3][4].

In gastrointestinal endoscopy, several CNN architectures have been successfully applied to classify pathological findings from endoscopic images. Models such as VGG16, ResNet50, DenseNet121, InceptionV3, Xception, and EfficientNet have significantly improved diagnostic performance by exploiting transfer learning techniques. Transfer learning allows pre-trained models to adapt to specific medical tasks using relatively small annotated datasets, thereby reducing training time and improving model generalization.

Despite these advances, automatic gastrointestinal disease classification remains challenging due to variations in illumination, image quality, lesion morphology, camera viewpoint, and the visual similarity between different pathological categories. In addition, the limited availability of large, well-annotated medical datasets increases the risk of overfitting and limits the robustness of deep learning models. Consequently, developing efficient and reliable computer-aided diagnosis systems remains an active area of research.

This study proposes a deep transfer learning framework based on the **EfficientNet-B4** architecture for the automatic classification of gastrointestinal diseases from endoscopic images. The proposed approach employs the **Kvasir-v2** dataset and integrates image preprocessing, data augmentation, and progressive fine-tuning to enhance feature extraction and improve classification performance. EfficientNet-B4 was selected because of its balanced compound scaling strategy, which provides an excellent trade-off between predictive accuracy and computational efficiency compared with conventional CNN architectures.

OBJECTIVES

The rapid advancement of **artificial intelligence (AI)**, particularly **deep learning**, has created new opportunities for the automated analysis of medical images. In gastrointestinal endoscopy, gastroenterologists must interpret a large number of images under time constraints, increasing the risk of human error. As reported by **Leufkens et al.** [38], adenoma detection rates during colonoscopy vary considerably among endoscopists, highlighting the need for reliable and reproducible computer-aided diagnostic systems.

Convolutional Neural Networks (**CNNs**) have become the state-of-the-art approach for the automatic recognition of anatomical structures and gastrointestinal lesions from endoscopic images [2] [3]. Rather than replacing clinicians, these systems are designed to assist clinical decision-making by identifying potential abnormalities, reducing the cognitive workload of physicians, and improving diagnostic consistency.

The primary motivation of this work is to reduce diagnostic errors in gastrointestinal endoscopy. In particular, **false-negative** predictions—where a pathological lesion is missed—may have serious clinical consequences, especially for colorectal polyps with malignant potential, whose early detection and resection are essential for preventing colorectal cancer . Consequently, improving polyp detection remains a key objective for enhancing the quality and reliability of colonoscopic examinations.

The main contributions of this work are summarized as follows:

- Development of an automated framework for gastrointestinal disease classification using transfer learning.
- Fine-tuning of the EfficientNet-B4 architecture to improve diagnostic performance on endoscopic images.
- Integration of image preprocessing and data augmentation techniques to enhance model robustness and reduce overfitting.
- Comprehensive experimental evaluation using the Kvasir-v2 dataset and standard classification metrics.
- Demonstration of the effectiveness of EfficientNet-B4 as a computer-aided diagnostic tool for gastrointestinal disease identification.

RELATED WORKS

The rapid advancement of artificial intelligence has significantly transformed the field of medical image analysis, particularly in gastrointestinal (GI) endoscopy. Deep learning-based computer-aided diagnosis (CAD) systems have demonstrated remarkable potential in assisting clinicians by improving diagnostic accuracy, reducing interpretation time, and minimizing inter-observer variability. Recent studies have focused on exploiting convolutional neural networks (CNNs) and transfer learning techniques to classify gastrointestinal diseases from endoscopic images.

Early computer-aided diagnostic systems relied on handcrafted feature extraction methods, including texture descriptors, color histograms, edge detection, and shape analysis, followed by conventional machine learning classifiers such as Support Vector Machines (SVMs), Random Forests (RFs), and k-Nearest Neighbors (k-NN) [5][6]. Although these methods achieved satisfactory performance on relatively simple datasets, they were highly dependent on manual feature engineering and exhibited limited robustness when confronted with complex clinical images containing large variations in illumination, viewpoint, lesion morphology, and image quality. These limitations motivated the adoption of deep learning approaches capable of automatically learning hierarchical visual representations.

With the emergence of deep convolutional neural networks, transfer learning has become the dominant strategy for gastrointestinal image classification. Pre-trained models such as VGG16, ResNet50, DenseNet121, InceptionV3, Xception, MobileNet, and EfficientNet have been successfully adapted to endoscopic image datasets, allowing researchers to achieve high classification performance while reducing training time and the need for large annotated datasets. The Kvasir and HyperKvasir datasets have become widely used benchmarks for evaluating these models [7] [8].

Among recent CNN architectures, EfficientNet has attracted considerable attention because of its compound scaling strategy, which jointly optimizes network depth, width, and input resolution. This balanced design enables EfficientNet models to achieve excellent predictive performance with fewer parameters than many traditional CNNs. A recent study proposed an EfficientNet-based framework with transfer learning for gastrointestinal disease detection on the Kvasir dataset, demonstrating that EfficientNet provides competitive accuracy while maintaining computational efficiency [9] [10] [11].

Several researchers have also explored hybrid and attention-based architectures to improve diagnostic performance. Attention mechanisms enable models to focus on clinically relevant regions, whereas ensemble learning combines multiple classifiers to enhance robustness and reduce prediction errors. These techniques have demonstrated improvements in lesion classification, especially for visually similar gastrointestinal abnormalities, although they generally require higher computational resources and more complex optimization procedures.

More recently, Vision Transformers (ViTs) and hybrid CNN–Transformer architectures have emerged as promising alternatives to conventional CNNs. By modeling long-range dependencies between image regions, transformer-based models can capture global contextual information that is difficult to represent using convolutional layers alone. Nevertheless, their effectiveness often depends on the availability of large-scale annotated datasets and considerable computational resources, limiting their practical deployment in many healthcare settings.

Despite these advances, several challenges remain. Gastrointestinal lesions frequently exhibit strong inter-class similarity and high intra-class variability. Variations in illumination, camera angle, image quality, and anatomical appearance further complicate automatic classification. In addition, class imbalance and limited annotated medical datasets continue to affect the generalization capability of deep learning models. These limitations highlight the importance of robust transfer learning strategies combined with effective preprocessing and data augmentation techniques. [12]

Motivated by these challenges, the present study proposes an automatic gastrointestinal disease classification framework based on **EfficientNet-B4** and transfer learning. Unlike many existing studies that evaluate several lightweight CNN architectures or focus on binary classification, this work investigates the capability of EfficientNet-B4 to perform reliable multiclass classification on the **Kvasir-v2** dataset. By integrating image preprocessing, data augmentation, and progressive fine-tuning, the proposed framework aims to improve classification performance while maintaining computational efficiency suitable for computer-aided diagnosis applications.

METHODS

The experiments conducted in this study were based on a publicly available gastrointestinal endoscopic image dataset containing representative images of different gastrointestinal diseases.

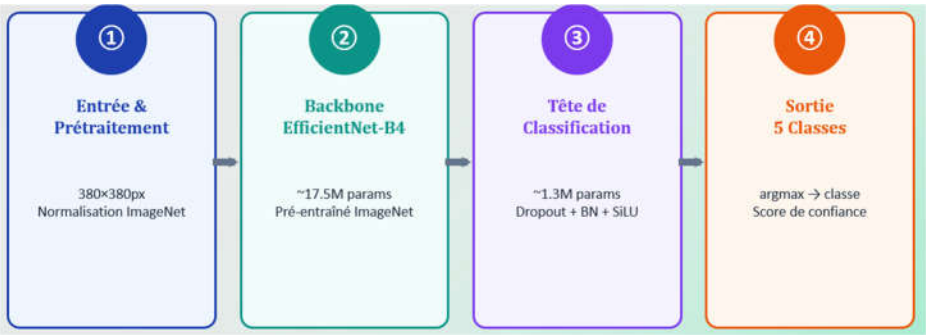

Figure 1. Architecture of classification system

Dataset Description

The **Kvasir-v2** dataset is a benchmark resource in the field of automated endoscopic image analysis. It was developed and released by the **Simula Research Laboratory** (Norway) in 2017 under the supervision of **Pogorelov et al.** [13]. The dataset was collected from real clinical endoscopic procedures, making it highly representative of real-world medical practice. The five selected classes represent either active pathological conditions or a healthy anatomical reference (anchor class), in accordance with the clinical objectives of this study.

Table 1. Clinical Characteristics of the Selected Kvasir-v2 Classes.

	Class	Clinical Description	Number of Images	Category
1	**Dyed-Lifted Polyps**	Polyps stained and elevated following submucosal injection. These images facilitate the assessment of resection margins during polypectomy procedures.	1000	Pathological
2	**Esophagitis**	Inflammation of the esophagus associated with **gastroesophageal reflux disease (GERD)**. Characterized by visible mucosal erosions of varying severity.	1000	Pathological
3	**Normal Pylorus**	Normal physiological appearance of the pylorus, the junction between the stomach and the duodenum. This class serves as the anatomical reference (healthy) class.	1000	Normal Anatomy
4	**Polyps**	Unstained colorectal mucosal polyps. These precancerous lesions carry a high risk of malignant transformation if not detected and treated early.	1000	Pathological
5	**Ulcerative Colitis**	Chronic inflammatory disease of the colon characterized by diffuse mucosal ulceration. Long-term clinical management is essential.	1010	Pathological
Total			**5010**	

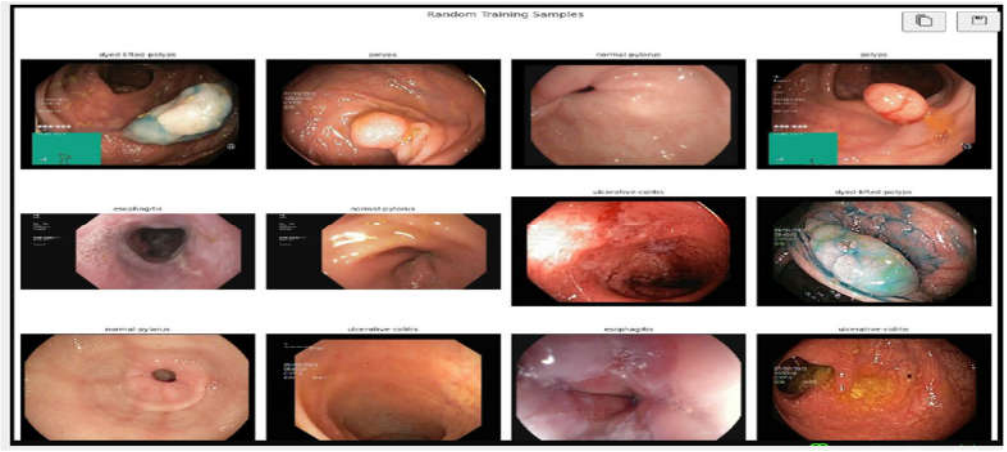

Figure 2. Representative Endoscopic Images for Each Class

Stratified 70/15/15 Data Partitioning

The complete dataset, consisting of **5010 endoscopic images**, was divided into three mutually exclusive subsets following a **stratified 70/15/15 split**, ensuring that the class distribution was preserved across the training, validation, and test sets. [14]

Data Augmentation Pipeline

To reduce the risk of **overfitting** and improve the model's **generalization capability**, a set of random data augmentation techniques was applied **exclusively to the training set** [15][16]. These transformations artificially simulate the variability encountered under different endoscopic image acquisition conditions, enabling the model to learn more robust and invariant feature representations.

Table 2. Data Augmentation Pipeline Transformations and Clinical Rationale for Each Technique.

Transformation	Parameters	Clinical Justification
Resize → CenterCrop	420 × 420 → 380 × 380 px	Adjusts the input to the native resolution required by **EfficientNet-B4**; center cropping removes the dark borders introduced by the endoscope.
RandomHorizontalFlip	$p = 0.5$	Endoscopic images have no canonical horizontal orientation; the endoscope can rotate freely during the examination.
RandomVerticalFlip	$p = 0.5$	Same rationale as above; vertical symmetry does not affect the diagnostic interpretation.
RandomRotation	±20°	Simulates angular variations of the endoscope during clinical procedures.
ColorJitter	brightness = 0.3, contrast = 0.3, saturation = 0.2, hue = 0.05	Models variations in clinical illumination, such as specular reflections and underexposure.
ToTensor + Normalize	μ = [0.485, 0.456, 0.406], σ = [0.229, 0.224, 0.225]	Standard **ImageNet** normalization required for compatibility with pretrained model weights.
RandomErasing	$p = 0.2$	Encourages the model to focus on distributed features, improving robustness to local artifacts such as air bubbles and mucus.

This study proposes a deep learning framework for the automatic classification of gastrointestinal pathologies from endoscopic images using transfer learning. Experiments were conducted on the **Kvasir-v2** benchmark dataset, from which five clinically relevant classes were selected: **Dyed-Lifted Polyps, Esophagitis, Normal Pylorus, Polyps,** and **Ulcerative Colitis**, comprising a total of **5,010 images**.

The proposed classification model is based on **EfficientNet-B4** pretrained on **ImageNet**. The original classification layer was replaced with a customized classification head composed of fully connected layers, Batch Normalization, SiLU activation, and Dropout to enhance feature discrimination and regularization.

Training was performed using a **two-phase progressive fine-tuning strategy[17]**. In the first phase, the EfficientNet-B4 backbone was frozen while only the classification head was optimized. In the second phase, the upper layers of the backbone were selectively unfrozen and fine-tuned using differential learning rates to improve feature adaptation while preserving pretrained representations. Additional regularization techniques, including mixed-precision training and class imbalance handling, were incorporated to improve convergence and generalization.

Phase 1: Warm-Up (Frozen Backbone)

During the first training phase, all parameters of the **EfficientNet-B4** backbone were frozen (requires_grad = False), while only the custom classification head (approximately **921K trainable parameters**) was optimized. This warm-up stage initializes the newly added classifier with feature representations extracted from the pretrained backbone without altering the weights learned from **ImageNet**.
This strategy offers two main advantages. First, it prevents the large gradients produced by a randomly initialized classifier from disrupting the pretrained backbone during the early stages of training. Second, training only the classification head converges rapidly (typically within **10–15 epochs**), providing a stable and effective initialization before proceeding to partial fine-tuning of the backbone.

Phase 2: Partial Backbone Fine-Tuning

In the second training phase, the **last four MBConv blocks** of the pretrained **EfficientNet-B4** backbone were unfrozen and fine-tuned using a **reduced learning rate**. This selective fine-tuning strategy adapts the high-level semantic features to the specific characteristics of endoscopic images while preserving the low-level representations learned from **ImageNet**, such as edge and texture detectors.
To ensure stable optimization, the unfrozen backbone layers were trained with a learning rate **ten times lower** than that of the classification head ($\mathbf{1 \times 10^{-5}}$), enabling gradual adaptation of the pretrained weights and improving generalization without disrupting previously learned representations.

Regularization Techniques

To improve generalization and reduce overfitting, several complementary regularization techniques were employed during training. These included **Dropout** (p = 0.3) to reduce neuron co-adaptation, **Batch Normalization** to stabilize training and accelerate convergence, **gradient clipping** (*max_norm* = 1.0) to prevent exploding gradients, and **Early Stopping** (*patience* = 7) to restore the best-performing model when validation loss no longer improved. In addition, the **ReduceLROnPlateau** scheduler progressively decreased the learning rate when validation performance plateaued, while **AdamW** optimization with **weight decay** (1×10^{-4}) provided L2 regularization to enhance model generalization.

RESULTS

Evaluation Metrics

Model performance was assessed on the independent **test set (752 images)** using several standard metrics for multi-class medical image classification. These include **overall accuracy**, **precision**, **recall (sensitivity)**, and **F1-score** for each class. To provide a balanced evaluation across all categories, both **macro** and **weighted F1-scores** were reported. The model's discriminative ability was further assessed using the **one-vs-rest ROC–AUC** for each class. Finally, a **normalized confusion matrix** was used to analyze class-wise classification performance and identify inter-class misclassifications. These complementary metrics provide a comprehensive assessment of the proposed model's accuracy, robustness, and clinical reliability.

Quantitative Results on the Test Set

The final evaluation was performed on the independent **test set (752 images)** using the best model obtained during **Phase 2** of training (**best_stage2.pth**, **epoch 18**), which achieved a **validation accuracy of 98.27%**. Model performance was assessed using a comprehensive classification report, including **precision, recall, F1-score**, and **support** for each class, providing a detailed evaluation of the classification performance across all five categories

Quantitative Results

The proposed model achieved an **overall accuracy of 98.40%**, a **macro F1-score of 98.39%**, and a **weighted F1-score of 98.39%** on the independent **test set (752 images)**, corresponding to a **1.60% classification error rate** (12 misclassified images).
Class-wise analysis demonstrated consistently high performance across all categories.
Dyed-Lifted Polyps achieved a **precision of 0.98**, **recall of 1.00**, and **F1-score of 0.99**, indicating perfect sensitivity with no missed cases.
Esophagitis showed the most robust performance, with **precision = 0.99**, **recall = 1.00**, **F1-score = 0.99**, and an **AUC of 1.00**, resulting in zero false negatives.
Normal Pylorus also achieved near-perfect performance (**precision = 0.99**, **recall = 0.99**, **F1-score = 0.99**), with only one image misclassified as esophagitis, representing a clinically negligible error
Polyps represented the most challenging class, achieving a **precision of 1.00**, **recall of 0.93**, and an **F1-score of 0.97**. This class accounted for **9 of the 12** total misclassifications, with most false negatives confused with **Ulcerative Colitis** (5 cases),
Ulcerative Colitis achieved a **precision of 0.97**, **recall of 0.99**, and an **F1-score of 0.98**. Only **2 of 152** ulcerative colitis images were missed, while the slightly lower precision resulted primarily from **five polyp images** being misclassified as ulcerative colitis. Given that both conditions require endoscopic evaluation and management, these errors remain clinically acceptable.

DISCUSSION

Comparison with Existing Literature

To evaluate the effectiveness of the proposed approach, the performance of the **EfficientNet-B4** model was compared with previously published studies on the same **Kvasir-v2** dataset. The comparison was based on the most representative evaluation criteria, including the **dataset**, **model architecture**, **classification accuracy**, and **F1-score**.

Table 3. Comparison of the Proposed EfficientNet-B4 Model with State-of-the-Art Methods on the Kvasir-v2 Dataset.

Study	Year	Architecture / Method	Dataset	Accuracy	F1-Score
Pogorelov et al. [13]	2017	Conventional CNNs (VGG, ResNet)	Kvasir-v2	83–86%	—
Tanbir et al. [18]	2021	EfficientNet (fine-tuning)	Kvasir-v2	93.5%	93.2%
Gunasekaran et al. [19]	2023	Ensemble: DenseNet201 + InceptionV3 + ResNet50 (weighted averaging)	Kvasir-v2	95.00%	~95%
Gebreslassie et al. [20]	2025	Stacking Ensemble (ResNet50 + DenseNet201 + MobileNet)	Kvasir-v2	94.33%	—
Proposed Model	**2026**	**EfficientNet-B4 (two-stage progressive fine-tuning + targeted data augmentation)**	**Kvasir-v2**	**98.40%**	**98.39%**

The proposed fine-tuned EfficientNet-B4 model achieved an overall accuracy of 98.40% and a macro F1-score of 98.39%, significantly outperforming all previously published methods evaluated on the same Kvasir-v2 dataset. Compared with the best reported result (Tanbir et al., 93.5% accuracy), our approach improves classification performance by 4.9 percentage points. This performance gain can be attributed to the combination of a two-stage progressive fine-tuning strategy, a targeted data augmentation pipeline, and mixed-precision training, which together enhance feature learning, improve model generalization, and optimize computational efficiency.

CONCLUSION

This work presented the complete implementation and experimental evaluation of the proposed automated gastrointestinal disease classification system developed in this study. The main contribution lies in the application of a **two-stage progressive transfer learning strategy** based on **EfficientNet-B4**, a state-of-the-art convolutional neural network whose compound scaling architecture is particularly well suited to the complex visual characteristics of endoscopic images.

The proposed framework integrates a coherent set of methodological components, including image preprocessing at the model's native input resolution (**380 × 380 pixels**), a targeted data augmentation pipeline designed to simulate the variability of clinical endoscopic images, robust class imbalance handling through weighted **Cross-Entropy Loss**, differential fine-tuning of the backbone network, and a comprehensive evaluation using multi-class performance metrics and **ROC** analysis.

The final experimental results—**98.40% accuracy**, **98.39% macro F1-score**, **98.39% weighted F1-score**, and an **average ROC–AUC of 99.80%**—demonstrate the effectiveness and robustness of the proposed approach. These results were achieved with only **12 misclassified images out of 752 test samples**, highlighting the model's excellent generalization capability. Furthermore, the proposed method outperformed previously published approaches on the **Kvasir-v2** dataset, confirming its competitiveness and its potential for reliable computer-aided diagnosis in gastrointestinal endoscopy.

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