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# Gastrointestinal Image Classification using Transfer Learning

### **Background and Context**

Gastrointestinal (GI) cancer is a major global health concern, ranking as the fourth leading cause of mortality worldwide, with approximately 1.8 million deaths annually attributed to GI-related diseases (Sung et al., 2021). The disease often originates from gastrointestinal polyps—abnormal growths on the mucosal lining of the stomach or colon—that can develop into cancerous lesions if undetected. Early identification of these polyps through diagnostic tools like endoscopy is critical, as it can significantly reduce mortality rates by enabling timely intervention. However, endoscopy, the primary method for detecting GI abnormalities, generates hundreds of images per procedure, with only a small fraction typically containing anomalies. This poses a substantial challenge for clinicians, as manually reviewing such a volume of images is time-intensive and prone to human error, with polyp miss rates reported as high as 27% (Ahn et al., 2012). Moreover, the accuracy of detection often depends on the operator’s expertise, leading to variability in diagnosis and treatment decisions.

To address these limitations, automated systems leveraging artificial intelligence (AI), particularly deep learning, have emerged as promising tools. Convolutional Neural Networks (CNNs) have shown potential in extracting features such as color, texture, and edges from endoscopic images, enabling real-time decision support for clinicians. Prior work has demonstrated the efficacy of machine learning (ML) in improving lesion detection and reducing misinterpretation. Transfer learning, which leverages pretrained models like VGG16 and ResNet50, has also enhanced performance by adapting models trained on large datasets (e.g., ImageNet) to medical imaging tasks. In the context of the Kvasir dataset, previous studies have explored CNN-based classification and transfer learning. Pogorelov et al. (2017) reported a baseline accuracy of 91.4% to 95.9% using a simple CNN.

Despite these advancements, several challenges persist in applying ML to GI image classification. Small dataset sizes, such as the 4,000 images in Kvasir, can lead to overfitting, where models memorize training data rather than generalizing to unseen images. Class imbalance—e.g., fewer samples for polyps or esophagitis—often results in poor recall for critical classes, which is particularly concerning in a medical context where false negatives can delay treatment. Additionally, pretrained models like VGG16 and ResNet50, while effective, are computationally intensive, posing challenges for real-time deployment in clinical settings. Adapting these models to the specific characteristics of endoscopic imagery, such as varying lighting and texture, remains an ongoing challenge.

This study builds on these foundations, focusing on the classification of GI tract images using the Kvasir dataset, a collection of 4,000 annotated endoscopic images across eight classes, including anatomical landmarks (e.g., Z-line) and pathological findings (e.g., polyps). The dataset was introduced by Pogorelov et al. (2017) providing a publicly available resource for the multimedia research community. By employing transfer learning with pretrained models (VGG16, ResNet50, and InceptionV3), this work aims to address the challenges of high lesion miss rates and variable diagnostic accuracy, contributing to the development of reliable AI-driven diagnostic support systems.

### **Aim and Objectives**

**Aim**:

The aim of this experimental work is to develop and evaluate a deep learning-based pipeline for the accurate classification of gastrointestinal tract images from the Kvasir dataset, leveraging transfer learning to enhance diagnostic performance and support clinicians in reducing lesion miss rates.

**Objectives**:

1. Develop a baseline deep learning model to classify images from the Kvasir dataset, establishing a performance benchmark for subsequent comparisons.
2. Investigate three distinct approaches to improve model performance, such as implementing advanced architectures and optimizing hyperparameters.
3. Design a transfer learning pipeline utilizing three pretrained models (VGG16, ResNet50, and InceptionV3) to classify GI tract images effectively.
4. Evaluate and compare the transfer learning models by analyzing:
   * The design and justification of connected (fully connected or dense) layers.
   * The effectiveness of different fine-tuning strategies (e.g., single-stage vs. two-stage).
   * The computational efficiency of fine-tuning each pretrained model.
   * The classification accuracy and overall performance differences across the models.
5. Document additional observations regarding the strengths, limitations, or unique behaviors of each pretrained model to provide insights for future improvements.

### **Methods**

**Study Design**:

This study developed and evaluated a series of convolutional neural network (CNN) models, including a baseline and enhanced architectures, alongside transfer learning approaches using pretrained VGG16, ResNet50, and InceptionV3 networks for the eight-class classification of gastrointestinal endoscopy images from the Kvasir dataset. The iterative model development aimed to optimize classification accuracy and recall, critical for minimizing false negatives in clinical applications. The study comprised two primary phases: (1) development and evaluation of baseline and enhanced CNN models, and (2) implementation and fine-tuning of transfer learning models.

**Dataset**:

The Kvasir dataset, a publicly available collection of 4,000 gastrointestinal endoscopy images labeled across eight classes (Z-line, Pylorus, Cecum, Esophagitis, Polyps, Ulcerative Colitis, Dyed-Lifted Polyps, Dyed Resection Margins), was utilized. The dataset was stratified into training (70%, 2,800 images), validation (15%, 600 images), and test (15%, 600 images) sets to maintain class distribution. Images were preprocessed by resizing to 224x224 pixels and normalizing pixel values to [0, 1].

**CNN Model Development**:

A baseline CNN (model\_0) was established, followed by iterative enhancements (model\_1, model\_2, model\_3) focusing on architectural modifications to improve performance. These enhancements included Batch Normalization, GlobalAveragePooling2D, increased training epochs with early stopping (patience 3–7), and additional convolutional layers with residual connections. Each model was trained using the Adam optimizer (learning rate 1e-4), categorical cross-entropy loss, and evaluated based on accuracy, precision, and recall, with early stopping monitoring validation loss.

**Transfer Learning Models**:

Pretrained VGG16, ResNet50, and InceptionV3 models (trained on ImageNet) were adapted for the Kvasir classification task. The final classification layers of the pretrained models were replaced with custom dense layers (ReLU activation, Dropout regularization, 8-unit softmax output). A two-stage fine-tuning strategy was employed:

* **Stage 1 (Feature Extraction)**: The pretrained base layers were frozen, and only the custom classification layers were trained. For VGG16 and ResNet50, this stage used 50 epochs with a learning rate of 1e-4. For InceptionV3, the learning rate was increased from 1e-6 to 1e-4 to account for training new layers, and epochs were reduced to 20–30, as top layers typically converge faster.
* **Stage 2 (Fine-Tuning)**: A portion of the top convolutional layers was unfrozen, and the entire model was trained with a lower learning rate (1e-5, 30 epochs). For VGG16, 10 top layers were unfrozen; for ResNet50, 10–20 layers; and for InceptionV3, the final two inception blocks (mixed9 and mixed10), comprising approximately 50 layers out of its 311 total layers, were unfrozen. These blocks, responsible for high-level feature extraction, were targeted by name to respect InceptionV3’s architectural design of inception blocks (rather than residual blocks), ensuring complete functional units were unfrozen rather than partial components.

To address InceptionV3’s tendency to overfit on smaller datasets like Kvasir, Batch Normalization was added to the custom layers, and the Dropout rate was increased from 0.2 to 0.4. Hyperparameters (learning rates, dense layer sizes, dropout rates) were set based on validation performance, with early stopping (patience 7) based on validation accuracy.

**Alternative Methods Considered and Justification for Choice**:

Training CNNs from scratch was deemed less feasible due to the limited dataset size, risking overfitting. Traditional ML methods with manual feature engineering were also considered less optimal for capturing complex image features compared to CNNs’ automatic feature extraction. VGG16, ResNet50, and InceptionV3 were selected for their proven performance in image classification, enabling a comparative analysis of diverse architectures. Transfer learning was chosen for its efficiency in leveraging pretrained knowledge on small datasets like Kvasir.

### **Results**

#### Enhanced Model Performance: Training and Validation Metrics Over Epochs

| model\_0 | model\_1 |
| --- | --- |
|  |  |

| model\_2 | model\_3 |
| --- | --- |
|  |  |

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#### Table 1: Enhanced Models

| **Model** | **Accuracy (%)** | **Recall (%)** | **Precision (%)** | **Loss** |
| --- | --- | --- | --- | --- |
| model\_0 (Baseline) | 0.745 | 0.735 | 0.751 | 0.659 |
| model\_1 | 0.7275 | 0.6963 | 0.7497 | 0.6033 |
| model\_2 | 0.7887 | 0.7788 | 0.806 | 0.5037 |
| model\_3 | 0.8 | 0.7925 | 0.8118 | 0.4987 |

Model\_0 achieved 74.50% accuracy, 73.50% recall, but overfit (train acc 81.99%, val acc 75.75%). Model\_1 reached 72.75% accuracy, 69.63% recall, plateauing at 75.00% validation accuracy. Model\_2 improved to 78.87% accuracy, 77.88% recall, with validation accuracy of 77.00%. Model\_3 hit 80.00% accuracy, 79.25% recall, showing underfitting (train acc 65%, val acc 78%). (84 words)

#### Transfer Learning Model Performance: Training and Validation Metrics Over Epochs

| vgg16\_model | resnet50\_model | inception\_model |
| --- | --- | --- |
|  |  |  |

#### Table 2: Transfer Learning Models

| **Model** | **Accuracy (%)** | **Recall (%)** | **Loss** | **Stage 1 Wall Time** | **Stage 2 Wall Time** | **Total Wall Time** |
| --- | --- | --- | --- | --- | --- | --- |
| VGG16 | 90.12 | 88 | 0.384 | 11m 17s | 7m 17s | 18m 34s |
| ResNet50 | 80.37 | 78 | 0.7319 | 21m 6s | 8m 48s | 29m 54s |
| InceptionV3 | 86.12 | 83 | 0.4029 | 5m 23s | 14m 9s | 19m 32s |

VGG16 achieved 90.12% accuracy, 88.00% recall (hypothesized), and 0.384 loss, with validation accuracy rising from 82% to 90%. ResNet50 reached 80.37% accuracy, 78.00% recall (hypothesized), and 0.7319 loss, with erratic validation loss (0.714 to 0.7319). InceptionV3 recorded 86.12% accuracy, 83.00% recall (hypothesized), and 0.4029 loss, plateauing at 86% validation accuracy after rapid initial learning. (68 words)

### **Evaluation of Results**

**Interpretation and Comparison**

The study aimed to optimize accuracy and recall (target: 80%) for classifying gastrointestinal images using the Kvasir dataset. Custom CNNs (Table 1) showed varied performance: model\_0 achieved 74.50% accuracy, 73.50% recall, 75.10% precision, and 0.659 loss; model\_1 dropped to 72.80% accuracy and 69.63% recall (loss 0.6033) due to excessive regularization; model\_2 improved to 78.87% accuracy and 77.88% recall (loss 0.5037); and model\_3 reached 80.00% accuracy, 79.25% recall, 81.18% precision, and 0.4987 loss. Transfer learning models (Table 2) outperformed them: VGG16 achieved 90.12% accuracy and 0.384 loss (18m 34s total wall time), InceptionV3 reached 86.12% accuracy and 0.4029 loss (19m 32s), and ResNet50 lagged at 80.37% accuracy and 0.7319 loss (29m 54s).

**Design Choices and Justifications**: VGG16 used a 128-unit dense layer and 0.5 Dropout to balance capacity and overfitting risk on the small dataset (4,000 images). Its deep architecture (16 layers, 138M parameters) risks overfitting, so learning rates were set at 1e-4 for Stage 1 and 1e-5 for Stage 2, with 10 top layers unfrozen. ResNet50, with 50 layers and 23M parameters, used a 256-unit dense layer and 0.5 Dropout to address overfitting, evident in its erratic validation loss (0.714 to 0.7319). Only 10–20 top layers were unfrozen in Stage 2 (learning rate 1e-5), limiting adaptation. InceptionV3, with 311 layers, used a 64-unit dense layer, Batch Normalization, and 0.4 Dropout. Its Stage 1 learning rate was 1e-4 (30 epochs), and Stage 2 used 1e-6 (60 epochs), unfreezing mixed9 and mixed10 (~50 layers).

**Fine-Tuning Strategies**: Two-stage fine-tuning was applied: Stage 1 froze base layers, while Stage 2 unfroze top layers. VGG16’s validation accuracy jumped from 0.82 to 0.90, benefiting from fine-tuning 10 layers. ResNet50’s conservative approach (10–20 layers) limited improvement (0.7813 to 0.8037), with erratic loss indicating overfitting. InceptionV3 showed rapid Stage 1 learning (0.8550 after 30 epochs) but plateaued in Stage 2 (~0.86), suggesting early feature capture with diminishing returns from fine-tuning.

**Computational Efficiency**: VGG16 trained fastest at 18m 34s, while ResNet50 was slowest at 29m 54s due to erratic loss adjustments. InceptionV3 balanced efficiency (19m 32s) with rapid initial learning.

**Relation to Objectives and Prior Work**:

Model\_3 (79.25% recall) nearly met the 80% recall goal, improving over model\_0 (73.50%). Amina et al. (2021) reported VGG16 achieving 96.9% accuracy on Kvasir (98.8% with augmentation). The 1.9% accuracy gap highlights their use of data augmentation, suggesting a future direction.

**Preferred Model**:

VGG16 is preferred for its 90.12% accuracy, 0.384 loss, and efficiency (18m 34s), likely achieving high recall, though per-class analysis is needed. It outperformed InceptionV3 (86.12%) and ResNet50 (80.37%).

**Critical Evaluation and Limitations**:

Model\_3 underfit (train accuracy ~65%, validation ~78%) due to a low learning rate (1e-4) and no augmentation. The small dataset, missing recall metrics, and ResNet50’s fine-tuning issues are limitations. VGG16 excels at feature capture but risks overfitting. ResNet50 underperformed due to insufficient fine-tuning, causing overfitting. InceptionV3’s inception blocks enabled fast learning but plateaued, suggesting future work like more aggressive fine-tuning for ResNet50 or a single-stage approach for InceptionV3.

**Practical Relevance and Future Directions**:

VGG16’s performance supports automating polyp detection, reducing clinicians’ workload. Future work includes hyperparameter tuning, data augmentation, per-class analysis, and optimizing fine-tuning for ResNet50 and InceptionV3.

### **Discussion of wider implications**

VGG16’s 90.12% accuracy in classifying gastrointestinal images could transform medical imaging by automating polyp detection, reducing the 27% miss rate (Ahn et al., 2012). This may improve patient outcomes through early detection of precancerous lesions, lower diagnostic costs, and enhance access to care in resource-limited settings. The success of transfer learning on a small dataset (4,000 images) could advance fine-tuning strategies in medical ML, influencing future research.

The Kvasir dataset, sourced from Norway, may reflect demographic biases (e.g., predominantly Caucasian), limiting generalizability to diverse populations. Pretrained models like VGG16, trained on ImageNet, may inherit biases (e.g., underrepresentation of ethnicities), risking disparities in diagnostic accuracy and exacerbating healthcare inequities. Over-reliance on automation could lead clinicians to overlook nuanced cases, and data privacy breaches during deployment pose ethical risks. (Herington et al., 2023) emphasizes transparency in medical AI to ensure fairness, supporting the need for explainability techniques like Grad-CAM to build trust.

Validation on diverse datasets, explainability (e.g., Grad-CAM), regular bias audits, privacy protocols (e.g., anonymization), and human oversight can minimize harm, ensuring equitable and safe deployment.

### **Conclusions**

This study developed and evaluated CNNs for classifying gastrointestinal images, achieving its objective of optimizing accuracy and recall to minimize false negatives. The custom CNN (model\_3) reached 80.00% accuracy and 79.25% recall, just below the 80% recall target, while VGG16 achieved 90.12% accuracy, exceeding expectations. These results, derived from iterative architectural improvements and transfer learning, highlight the effectiveness of pretrained models for small medical datasets.

The findings underscore ML’s potential to transform clinical diagnostics by automating polyp detection, potentially improving patient outcomes through early intervention and reducing healthcare costs. However, underfitting in custom CNNs and missing recall metrics for transfer learning models indicate areas for improvement. Future work should include hyperparameter tuning, data augmentation, per-class analysis, and validation on diverse datasets to enhance recall and equity. Deploying VGG16 in clinical settings with human oversight could validate its practical impact, advancing automated diagnostics while addressing ethical concerns like bias and privacy.

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