*Journal of Interdisciplinary Mathematics*
ISSN: 0972-0502 (Print), ISSN: 2169-012X (Online)
Vol. 28 (2025), No. 6, pp. 2071–2078
DOI : 10.47974/JIM-2348

# A structured mathematical approach to improving gastrointestinal disease classification with transfer learning

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## Abstract

The integration of AI into medical diagnostics has transformed the detection of gastrointestinal diseases. In this study, we develop a clear mathematical framework for classifying multiple GI conditions. We extend the GastroVision dataset by adding three specific classes—Inflammatory Conditions, Neoplastic Growths and Interventional Findings—and employ three state-of-the-art transfer-learning models (EfficientNetV2, Vision Transformer and Swin Transformer). Outputs from these models are combined using a stacking ensemble; we apply standard data-augmentation techniques and systematically tune each model's parameters to maximize performance. Our ensemble achieved an overall accuracy of 94.8%, with precision at 92.3%, recall at 93.7% and an F1-score of 93.0%, exceeding current benchmarks. Performance was strong across all categories, with the highest accuracy of 96.1% on Neoplastic Growths. These results demonstrate both the mathematical soundness and practical value of our approach. By linking rigorous model development to clinical applications, this work provides a reliable, extensible framework for deploying AI in complex diagnostic settings and has the potential to improve patient outcomes.

***Subject Classification:*** *68T07.*

***Keywords:*** *Gastrointestinal disease detection, Transfer learning, Ensemble learning, Mathematical optimization, Vision transformers (ViT) Swin transformers.*

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## 1. Introduction

Diagnosing gastrointestinal diseases is difficult because the GI tract varies in appearance and function. As the prevalence of GI disorders grows worldwide, especially in India, there is a need for faster and more accurate methods. Conventional diagnosis depends on manual interpretation of endoscopic images, which is both time-intensive and prone to error. Artificial intelligence offers a way to streamline this process and improve consistency. In this study, we enhance AI-based diagnostics by applying mathematical optimization to an ensemble of transfer-learning models. We extend the GastroVision dataset with three clinically relevant classes—inflammatory conditions, neoplastic growth and interventional findings. We employ EfficientNetV2, Vision Transformer and Swin Transformer to extract complementary features, then combine their predictions through a stacking ensemble. Systematic hyperparameter tuning ensures each model contributes effectively to the final decision.

Experimental results demonstrate robust multi-class classification, with an overall accuracy of 94.8% on the expanded dataset. These findings highlight the impact of rigorous model selection, parameter tuning and feature integration. By uniting mathematical methods with practical application, this work provides a solid foundation for future AI research in medical diagnostics.

In this work the GastroVision dataset used a well-established collection of annotated endoscopic images for GI disease detection. To improve its diagnostic value, we added three clinically important classes:

1. *Inflammatory Conditions:* Images showing redness, swelling, ulceration and tissue fragility, to capture signs of Crohn's disease, ulcerative colitis and other inflammatory disorders.
2. *Neoplastic Growths:* Images of polyps, masses and abnormal tissue formations, for early identification of benign and malignant lesions.
3. *Interventional Findings:* Post-procedure images displaying treated areas, healing tissues and any complications, to support assessment after therapeutic interventions.

These additions give the dataset a fuller range of GI presentations, strengthening model training and improving classification accuracy for real-world clinical use.

## 2. Mathematical Foundation

We use precise mathematical methods to improve feature extraction and ensemble learning for gastrointestinal disease detection. This section describes the equations behind how transfer-learning models extract features and how a stacking ensemble combines their outputs.

*Feature Extraction with Transfer Learning*

Feature extraction maps each endoscopic image into a high-dimensional feature space to capture the patterns needed for classification. We employ three pretrained architectures—EfficientNetV2, Vision Transformer (ViT) and Swin Transformer—for this task. In mathematical terms, feature extraction from image X.
X can be written as:

$$F(x) = fn\ (fn-1\ (\ldots f1(x)))$$

where:

$x \in RH \times W \times C$ is the input image of height H, width W, and channels C,

fk denotes the transformation performed by the $k^{th}$ layer of the model,

F(x) ∈ Rd is the extracted feature vector in d-dimensional space.

*Stacking Ensemble Learning*

The stacking ensemble method combines predictions from multiple base models to enhance overall classification performance. Let {M1,M2,…, Mn} denote n base models, each providing a probabilistic prediction vector Pi(x) for an input x, where:

$$Pi(x) = [pi1(x), pi2(x), \ldots, piC(x)],$$

with pij(x) representing the probability assigned by model Mi to class j, and C is the number of classes. The final prediction H(x) from the ensemble is computed using a meta-learner:

$$H(x) = \varnothing \sum_{k=1}^{n} ai\,.\,pi(x)$$

where:

αi are the learned weights for each base model,

ϕ(·) is the activation function of the meta-learner.

*Weight Optimization in the Ensemble*

To optimize the weights αi, the ensemble minimizes a loss function based on the difference between the true labels y and the predicted probabilities H(x). For a dataset of size N, the mean squared error (MSE) loss function is given by:

$$L = 1/N\sum_{k=1}^{n}(yk - H(xk))2$$

Gradient-based optimization techniques such as Adam are used to update αi\alpha_iαi iteratively:

$$\alpha it + 1 = \alpha it - \eta \cdot \partial \alpha it \partial L,$$

where: η is the learning rate, t is the iteration number.

## 3. Related Work

Gastrointestinal disease detection has advanced considerably through AI techniques, notably transfer learning and ensemble modeling. This section reviews two areas: feature-extraction approaches in medical imaging and ensemble-based strategies for disease classification. Key studies and their contributions are summarized in *Table 1.*

This work integrates recent advances in feature extraction and ensembles learning to address class imbalance and variability in

**Table 1**

**Summary of Related Work**

| Reference | Focus | Key Contribution |
|---|---|---|
| [1] | ResNet for medical imaging | Introduced residual learning for feature extraction. |
| [2] | EfficientNet for image classification | Optimized feature scaling for better accuracy. |
| [3] | CNNs for polyp detection | Applied CNNs to colonoscopy images for GI diagnostics. |
| [4] | Vision Transformers | Utilized self-attention for complex image analysis. |
| [5] | Ensemble for breast cancer detection | Combined CNNs and gradient boosting for improved accuracy. |
| [6] | GI cancer detection using ensembles | Integrated SVMs and CNNs for esophageal cancer detection. |

endoscopic images. By employing state-of-the-art transfer-learning models within a stacking ensemble, it delivers a more reliable framework for GI disease classification.

### 3.1 *Feature Extraction in Medical Imaging*

Effective feature extraction is essential for applying AI to medical imaging, especially in GI diagnostics. Transfer learning models pre-trained on large datasets such as ImageNet offer robust representations for endoscopic images. For example, ResNet [1] introduced residual connections, which facilitate training of deep networks and have become a standard choice for fine-tuning. EfficientNet [2] employs compound scaling to balance network depth, width and resolution, improving accuracy and efficiency in medical applications. In GI disease detection, Y. Tian et al. [3] fine-tuned a convolutional neural network on colonoscopy images to detect polyps, demonstrating transfer learning's practical benefits. More recently, Vision Transformers (ViT) [4][11] use self-attention to capture long-range image dependencies, enhancing feature richness in complex medical images.

### 3.2 *Ensemble Learning for Disease Detection*

Ensemble methods combine multiple models to boost prediction accuracy and robustness. Stacking ensembles, which train a meta-learner on the outputs of base models, have achieved strong results in medical diagnostics. Wu et al. [5] and Fontenla-Seco et al. [8] applied stacking to breast cancer detection by merging convolutional networks with gradient boosting, surpassing individual performance. In gastrointestinal diagnostics, Liang et al. [6] combined support vector machines and CNNs in an ensemble for esophageal cancer detection, addressing class imbalance and improving generalization. More recent work integrates architectures such as EfficientNet and Swin Transformer in a stacking framework [7][10], using meta-learners—often logistic regression or shallow neural networks—to weight and combine model predictions for optimal accuracy and stability [12][9].

## 4. Experimental Results

We evaluated our approach on the expanded Gastro-Vision dataset to measure its ability to identify GI conditions. Experiments compared each transfer-learning model (EfficientNetV2, Vision Transformer and Swin

Transformer) with the stacking ensemble. We used accuracy, precision, recall, F1-score and AUROC as our metrics.

**Table 2**

**Model performance**

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUROC |
|---|---|---|---|---|---|
| EfficientNetV2 | 92.3 | 90.5 | 91.0 | 90.7 | 0.94 |
| Vision Transformers | 93.1 | 91.8 | 92.4 | 92.1 | 0.95 |
| Swin Transformers | 93.8 | 92.7 | 93.0 | 92.8 | 0.96 |
| Stacking Ensemble | 94.8 | 93.2 | 93.7 | 93.4 | 0.97 |

Each model was trained separately on the augmented images. *Table 2* shows that each individual model performs strongly on the augmented dataset, with Swin Transformer leading among the base models (93.8 % accuracy, 92.8 % F1-score, 0.96 AUROC). EfficientNetV2 and Vision Transformer also achieve over 92 % accuracy and around 0.94–0.95 AUROC. Importantly, the stacking ensemble further improves every metric—reaching 94.8 % accuracy, 93.4 % F1-score and 0.97 AUROC—demonstrating that combining model outputs yields more precise and reliable predictions than any single architecture alone.

The introduction of three novel classes Inflammatory Conditions, Neoplastic Growths, and Interventional Findings was validated through class-specific performance metrics. The stacking ensemble model achieved superior accuracy and consistency in identifying these classes, as shown in *Table 3*.

**Table 3**

**Performance of the three new classes**

| Class | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Inflammatory Conditions | 94.2 | 92.5 | 93.0 | 92.7 |
| Neoplastic Growths | 96.1 | 94.8 | 95.2 | 95.0 |
| Interventional Findings | 94.0 | 92.7 | 93.4 | 93.0 |

The experimental results confirm the effectiveness of the proposed stacking ensemble framework, particularly for the three newly introduced classes. The stacking ensemble leveraged the strengths of individual transfer learning models, resulting in superior overall performance. These findings demonstrate the potential of the methodology for real-world clinical applications, where accurate and reliable GI disease detection is critical.

## 5. Conclusion

This work introduces a rigorous mathematical framework for multi-class gastrointestinal disease detection, built on an enhanced GastroVision dataset and a stacking ensemble of three advanced transfer-learning models: EfficientNetV2, Vision Transformer and Swin Transformer. By incorporating three new, clinically important classes—inflammatory conditions, neoplastic growth and interventional findings—we address shortcomings in current AI diagnostics. Our experiments demonstrate that the stacked ensemble consistently surpasses individual models, achieving 94.8 % overall accuracy and a 93.4 % F1-score, with 96.1 % accuracy on neoplastic growth. These results confirm the method's robustness and its potential for real-world clinical application. Beyond improving GI disease classification, the proposed approach offers a scalable template for other complex imaging tasks. Future work will extend this framework to additional imaging modalities and explore its integration into live clinical workflows, further advancing AI-driven diagnostic tools in healthcare.

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*Received December, 2024*