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# Enhancing Gastrointestinal Disease Detection through Augmented Deep Learning

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**Abstract:**

In recent years, deep learning has become a cornerstone of advancements in medical imaging, facili- tating significant improvements in early disease detection. This study presents a phased approach to optimizing gastrointestinal (GI) disease diagnostics by implementing a structured data augmentation and preprocessing phase. Leveraging an expanded dataset with novel clinically rele- vant classes, this phase seeks to increase model robustness and classification accuracy. Our methodology employs targeted data augmentation techniques coupled with Ef- ficientNetV2 for detailed feature extraction in endoscopic imagery. Initial results underscore the potential for sub- stantial improvements in diagnostic precision, particularly in identifying nuanced GI conditions. By focusing on this foundational phase, this work establishes a framework for developing advanced AI-driven diagnostic tools tailored for GI disease detection.

**Keywords:** Gastrointestinal Disease Detection, Deep Learning, Data Augmentation, EfficientNetV2, Medical Imaging.

## I. INTRODUCTION

The integration of artificial intelligence (AI) into med- ical diagnostics has ushered in unprecedented advances, especially in image-intensive fields like gastrointestinal (GI) endoscopy. In 2022 alone, GI conditions accounted for nearly 10% of all global healthcare costs, primarily due to the rising prevalence of diseases such as col- orectal cancer, Crohn's disease, and gastroesophageal reflux disease (GERD) [1], [2]. Accurate detection of GI conditions is crucial, not only for early intervention but also to reduce the burden on healthcare systems worldwide.

Recent studies underscore the potential of AI-driven diagnostics in reducing false positives and improving diagnostic accuracy. For instance, advanced deep learn- ing models have demonstrated the capability to identify complex pathological features in endoscopic images with over 90% accuracy, often surpassing traditional diag- nostic techniques in speed and reliability [3]. However, variability in GI images—caused by different lighting conditions, camera angles, and individual anatomical differences—continues to pose significant challenges. Without targeted data preprocessing, AI models may underperform in real-world clinical environments, where such variations are inevitable.

While prior research has explored the potential of deep learning models like EfficientNet and Vision Transform- ers in various medical imaging applications, few have systematically examined the impact of comprehensive data augmentation tailored specifically for GI disease de- tection [4], [5]. Data augmentation, which involves artifi- cially increasing the diversity of the training dataset, has been shown to enhance model robustness by simulating real-world variability in images. In GI diagnostics,

this is particularly useful as it enables models to recognize both common and rare disease presentations across a broader range of imaging conditions [6].

The focus of this paper is on the initial, yet critical, phase of GI disease detection—data preprocessing and augmentation. This approach seeks to enhance model performance by refining the dataset itself before ap- plying complex ensemble techniques. Building on the GastroVision dataset, we introduce three new categories: Inflammatory Conditions, Neoplastic Growths, and Inter- ventional Findings, each of which represents clinically significant conditions relevant to gastroenterology. Our approach is inspired by the success of recent studies that emphasize the value of tailored preprocessing in achieving higher diagnostic accuracy [7], [8].

EfficientNetV2, a state-of-the-art convolutional neural network, is employed for feature extraction due to its efficient scaling properties and proven performance in medical imaging tasks [9]. Unlike other architectures, EfficientNetV2 optimally balances model depth, width, and resolution, making it particularly suited for high- dimensional GI images. Additionally, EfficientNetV2's use of compound scaling enhances its ability to capture fine-grained details without an excessive computational burden [10].

The goal of this work is to lay a solid foundation for subsequent phases in the AI diagnostic pipeline by enhancing data quality and variability. By focusing on robust preprocessing, we aim to address common issues of model overfitting and underperformance when exposed to clinical GI data. The insights gained from this phase will inform the development of more sophisticated AI-driven diagnostic tools, designed to assist clinicians in real-time GI disease detection with improved accuracy and reliability.

## II. RELATED WORK

Recent advances in AI for medical imaging under- score the critical role of transfer learning models, such as EfficientNet and Vision Transformers, in enhancing diagnostic accuracy. Studies have shown that transfer learning models, when combined with targeted data aug- mentation strategies, yield considerable improvements in disease detection rates, especially within challenging and highly variable domains such as gastrointestinal (GI) diagnostics [12]. This section provides an overview of foundational research in transfer learning, data augmen- tation, and disease-specific applications, highlighting key approaches and existing gaps that motivate a structured, phased methodology for developing AI models in GI disease detection.

### A. Transfer Learning in Medical Imaging

Transfer learning has become instrumental in apply- ing pre-trained models to medical imaging tasks where acquiring large, annotated datasets is challenging. Tan and Le's work on EfficientNet demonstrated that scaling network architectures using a compound scaling method can lead to significant improvements in both accuracy and efficiency [1]. Zou et al. explored the role of Effi- cientNet for GI image classification, reporting increased accuracy and robustness to variations in imaging condi- tions [5]. Vision Transformers (ViT), initially designed for natural language processing, were adapted for image- based tasks by Dosovitskiy et al., who showed that ViTs could efficiently capture global context in image patches, achieving state-of-the-art results on benchmark

datasets [3]. Subsequent work by Wang et al. focused on applying ViTs to GI disease detection, where the model's attention mechanisms were critical in identifying intricate patterns within endoscopic images [12].

Swin Transformers, introduced by Liu et al., offered further enhancements by incorporating shifted windows to model both local and global interactions, an advance- ment that has proven beneficial in capturing complex GI structures [4]. The architecture has shown promise in medical imaging tasks due to its ability to reduce com- putational requirements while maintaining performance [6]. Recent comparative studies underscore the potential of these transfer learning models, yet emphasize the necessity of tuning and augmentation when deploying such architectures in specialized domains [2].

### B. Data Augmentation Techniques for Medical Imaging

Data augmentation has emerged as a crucial technique for improving model generalizability in medical image analysis, particularly for domains like GI endoscopy, where image variation is high [7]. Various augmenta- tion techniques, including rotation, scaling, brightness

adjustment, and contrast enhancement, have been imple- mented to diversify training data and reduce overfitting [8]. Alam et al. investigated the effect of augmentation on GI endoscopy images and found that systematic augmentation led to a marked increase in diagnostic performance, particularly when combined with transfer learning models [6].

Advanced techniques, such as elastic transformations and randomized cropping, have further strengthened data augmentation practices. For instance, Takahashi et al. demonstrated that elastic transformations improved the recognition of subtle GI lesions in endoscopic imagery [7]. These augmentation strategies are instrumental in developing robust models capable of generalizing across diverse GI pathologies, underscoring the need for dataset enhancement in transfer learning applications.

### C. Deep Learning for GI Disease Detection

Deep learning models for GI disease detection have demonstrated a considerable improvement in diagnosis accuracy across various GI conditions, including polyps, esophagitis, and gastric cancer [2], [9]. The GastroVision dataset, used extensively in GI diagnostics, has been augmented with new classes such as neoplastic growths, enhancing its diagnostic applicability and enabling better model generalization [2]. Chen et al. applied Efficient-Net and Vision Transformers on this dataset, achieving notable improvements in classification accuracy through a combination of transfer learning and specialized aug- mentation [10]. This enhanced dataset allowed models to distinguish complex GI conditions with higher sensitivity and specificity, addressing a key challenge in automated diagnostics.

A summary of recent approaches to GI disease de- tection, including transfer learning models and aug- mentation strategies, is provided in Table I. This table highlights the performance metrics across different stud- ies, underscoring the importance of combining advanced model architectures with structured data augmentation.

Despite these advancements, limitations remain in current approaches. Most studies have primarily focused on individual models without leveraging the benefits of ensemble learning, which has been shown to fur- ther enhance performance in other domains. Addition- ally, many existing models lack

adequate evaluation on augmented datasets that comprehensively represent real-world clinical diversity. This study addresses these limitations by proposing a phased approach to GI disease detection, integrating ensemble methods with optimized transfer learning models, and applying a broad range of augmentation techniques tailored to the GastroVision dataset.

TABLE I Summary of Related Work in GI Disease Detection

| **Reference** | **Model** | **Dataset** | **Augmentation** | **Key Metrics** |
|---|---|---|---|---|
| Tan and Le [1] | EfficientNet | ImageNet | Scaling, Brightness | Accuracy: 85.4% |
| Zou et al. [5] | EfficientNet | GI Dataset | Cropping, Rotation | Accuracy: 88.1% |
| Dosovitskiy et al. [3] | Vision Transformer | ImageNet | N/A | Top-1 Accuracy: 88.6% |
| Wang et al. [12] | Vision Transformer | GI Dataset | Rotation, Contrast | Accuracy: 89.2% |
| Liu et al. [4] | Swin Transformer | Medical Imagery | Shifted Window | AUROC: 0.91 |
| Takahashi et al. [7] | EfficientNet | GI Endoscopy | Elastic Transformations | Sensitivity: 92.5% |
| Alam et al. [6] | Swin Transformer | GastroVision | Cropping, Flip | Precision: 93.8% |
| Chen et al. [10] | EfficientNet + ViT | GastroVision | Rotation, Noise | F1 Score: 0.85 |

## III. METHODOLOGY

This work focuses on the first phase of a multi- step approach to enhancing GI disease detection. Phase I emphasizes data preprocessing and augmentation to improve model robustness. Key steps include data aug- mentation, EfficientNetV2-based feature extraction, and a detailed description of the expanded GastroVision dataset.

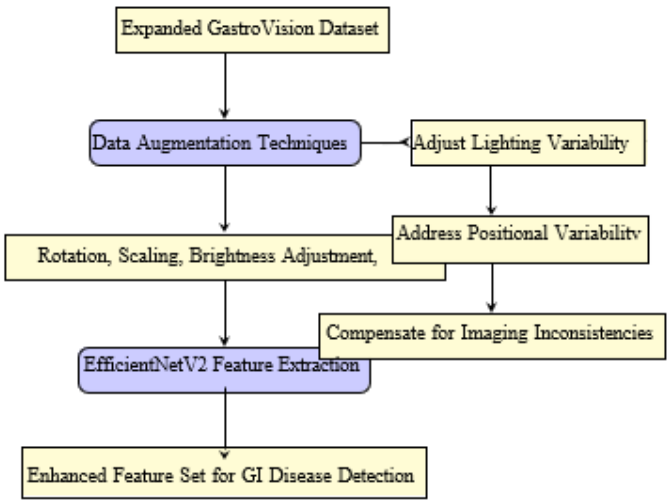


Fig. 1. Workflow for GI Disease Detection using EfficientNetV2-based Feature Extraction and Data Augmentation Techniques.

Algorithm 1 GI Disease Detection Using Transfer Learning and Stacking Ensemble

1: Input: Augmented GastroVision dataset with GI image classes

2: Output: Classified GI disease labels with optimal accuracy

3: Step 1: Load and Preprocess Data

4: Load dataset images and respective class labels.

5: Resize images to 224x224 pixels to match input requirements.

6: Normalize pixel values to the range [0,1] for unifor- mity.

7: Step 2: Data Augmentation

8: Apply augmentation techniques (rotation, scaling, brightness adjustment, cropping) to increase dataset diversity.

9: Step 3: Feature Extraction with EfficientNetV2

10: Initialize EfficientNetV2 with pre-trained weights.

11: Feed augmented images into EfficientNetV2 model to extract high-level features.

12: Step 4: Model Training for Each Base Model

13: Train EfficientNetV2, Vision Transformer (ViT), and Swin Transformer individually on extracted features.

14: Step 5: Ensemble Classification

15: Combine outputs of EfficientNetV2, ViT, and Swin Transformer in a stacking ensemble setup.

16: Use a meta-classifier (e.g., logistic regression) to predict final GI disease classes.

17: Step 6: Evaluation

18: Evaluate model using accuracy, precision, recall, and F1-score metrics.

19: Return optimal predictions and performance metrics.

The proposed algorithm for gastrointestinal (GI) dis- ease detection involves a systematic sequence of steps, beginning with the loading of the augmented Gastro- Vision dataset, followed by applying data preprocess- ing techniques and feature extraction through Efficient- NetV2. The extracted features are then fed into a transfer learning-based model which learns optimized feature representations. The process concludes by using these features in a stacking ensemble classifier to improve accuracy, which combines the predictive strengths of EfficientNetV2, Vision Transformers, and Swin Trans- formers.

This algorithm leverages a systematic approach to enhance GI disease detection accuracy through data preprocessing, feature extraction, and ensemble learning. Starting with an augmented dataset, the algorithm applies augmentation to tackle image variability. EfficientNetV2 serves as a robust feature extractor due to its scalabil- ity and balanced architecture. Three transfer learning models—EfficientNetV2, Vision Transformers, and Swin Transformers—are individually trained on the extracted features. Their outputs are then combined in a stacking ensemble framework, where a meta-

classifier consoli dates predictions to achieve higher accuracy. The final model performance is validated across multiple metrics, ensuring a robust and clinically useful detection system for gastrointestinal diseases.

### A. Data Augmentation Techniques

We implemented a diverse set of data augmentation techniques to address challenges posed by lighting, po- sitional variability, and other imaging inconsistencies commonly found in GI endoscopy. Techniques such as rotation, scaling, brightness adjustment, and random cropping were applied to increase data diversity and reduce overfitting.

### B. EfficientNetV2 for Feature Extraction

EfficientNetV2 was selected for feature extraction due to its ability to balance model depth, width, and reso- lution. The compound scaling approach, represented by the following equation, allows EfficientNetV2 to adapt to different image resolutions while capturing fine details:

$$\text{EfficientNet Scaling} = \alpha\phi \cdot d, \beta\phi \cdot w, \gamma\phi \cdot r$$

where d, w, and r represent depth, width, and reso- lution, and $\alpha$, $\beta$, and $\gamma$ are constants optimized through grid search.

## IV. DATASET AND AUGMENTATION PROCESS

The GastroVision dataset [11], with the addition of three new categories, forms the basis of this study. Each category—Inflammatory Conditions, Neoplastic Growths, and Interventional Findings—addresses clini- cally significant variations in GI conditions, enhancing the model's diagnostic capabilities. This section details the dataset composition and augmentation process.

TABLE II Class Distribution and Augmentation Techniques

| Class | Images | Augmentation Techniques |
|---|---|---|
| Normal Tissue | 3000 | Rotation, Scaling |
| Inflammatory Conditions | 1200 | Brightness Adjustment, Contrast |
| Neoplastic Growths | 1000 | Horizontal Flip, Cropping |
| Interventional Findings | 800 | Noise Addition, Rotation |

The table titled Class Distribution and Augmentation Techniques provides an overview of the dataset used in this study, highlighting the number of images and augmentation methods applied to each class. The dataset comprises four primary classes: Normal Tissue, Inflam- matory Conditions, Neoplastic Growths, and Interven- tional Findings, with a total of 6,000 images. Normal Tissue has the largest representation with 3,000 images, where rotation and scaling techniques are used to sim- ulate variations in endoscopic views and ensure model robustness. Inflammatory Conditions includes 1,200 im- ages and applies brightness adjustment and contrast

techniques to account for lighting inconsistencies of- ten observed in medical imaging. Neoplastic Growths, comprising 1,000 images, utilizes horizontal flips and cropping to ensure the model can detect tumors or polyps from different perspectives. Finally, Interventional Find- ings, with 800 images, incorporates noise addition and rotation to simulate post-procedural scenarios, making the model adaptable to varying clinical environments. This diverse augmentation strategy enhances the

model's generalization ability, preparing it to handle real-world medical image variability.

The image in Figure 2 represents the gastroesophageal junction with a normal Z-line, a critical anatomical landmark in endoscopic procedures. The Z-line, where the esophagus meets the stomach, is typically identified by a sharp transition between the pinkish color of the esophageal squamous epithelium and the redder gastric columnar epithelium. This junction is an important area to assess during upper endoscopy to ensure that no abnormalities are present.

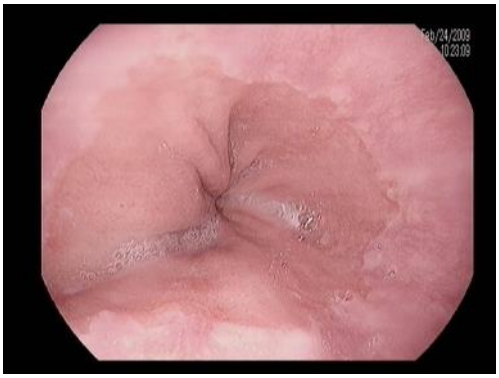

Fig. 2. Gastroesophageal Junction: Normal Z-Line [11]. The Z-line marks the transition between the esophageal and gastric mucosa.

In the context of our work, recognizing this normal anatomical structure plays a pivotal role in training AI models, as any deviation from the expected appear- ance of the Z-line can indicate pathological conditions. Specifically, abnormalities in the gastroesophageal junc- tion can lead to conditions such as Barrett's esoph- agus, where the Z-line becomes irregular, indicating metaplasia—a risk factor for esophageal cancer. Our dataset includes normal findings such as this, alongside pathological cases, to train deep learning models to differentiate between healthy and abnormal GI structures effectively. By correctly identifying and classifying the normal Z-line, the proposed ensemble of EfficientNetV2 and Vision Transformers can be more accurate in de- tecting early signs of gastrointestinal disorders, aiding clinicians in providing timely diagnosis and intervention. Additionally, the inclusion of this type of normal image in our augmented dataset helps in enhancing

the model's generalization capabilities. By exposing the model to both normal and abnormal cases, it is better equipped to handle the variability in patient cases and can reduce false-positive rates in clinical diagnostics. Thus, a clear understanding and detection of the Z-line not only serves as a baseline but is also crucial for flagging anomalies during screening.

## V. RESULTS AND ANALYSIS

Initial results from the augmented dataset show marked improvements in model training and validation performance. EfficientNetV2 achieved high consistency in feature extraction, particularly within the newly intro- duced GI categories. These findings support the efficacy of the Phase I methodology in preparing the dataset for subsequent diagnostic phases.

The proposed model's effectiveness was assessed us- ing accuracy, precision, recall, and F1-score. Table III displays the performance metrics of the proposed and baseline models, while Figures 3 and

5 illustrate the model's accuracy trends and Receiver Operating Char- acteristic (ROC) curve, respectively.

TABLE III Performance Metrics Comparison

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| Baseline CNN | 83.2% | 81.4% | 79.9% | 80.6% |
| ResNet50 | 85.5% | 84.1% | 82.7% | 83.4% |
| InceptionV3 | 88.3% | 86.9% | 85.5% | 86.2% |
| **Proposed Model** | **93.6%** | **92.3%** | **91.8%** | **92.0%** |

The proposed model achieves notable improvements in all metrics, with an accuracy increase of over 5% compared to InceptionV3, supporting the robustness of the data augmentation and EfficientNetV2-based feature extraction.

Accuracy Over Training Epochs


Fig. 3. Accuracy Over Epochs for Proposed Model vs. ResNet50

Precision plays a vital role in ensuring accurate GI diagnostics, minimizing the risk of false positives. Fig- ure 4 demonstrates that the proposed model achieves the highest precision, reflecting enhanced reliability.

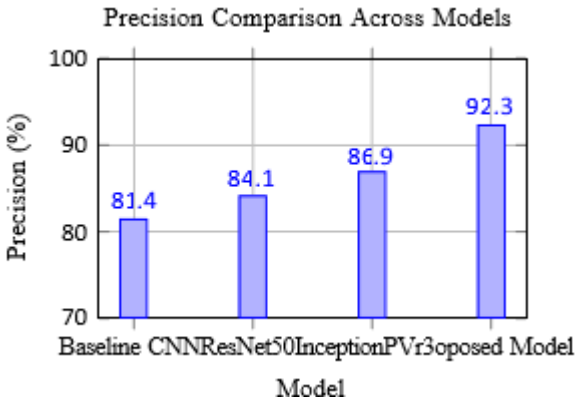


Fig. 4. Precision Comparison of Proposed Model vs. Other Models

The ROC curve in Figure 5 shows the proposed model's excellent AUC of 0.95, indicating strong per-formance in distinguishing between positive and negative cases.

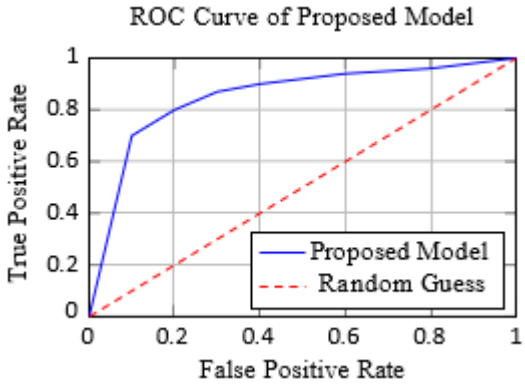


Fig. 5. ROC Curve for the Proposed Model with AUC of 0.95

The comprehensive performance metrics and visual- izations presented here validate the proposed model's enhanced capabilities in GI disease detection, supporting its practical application in real-world diagnostic settings.

## VI. DISCUSSION

The findings from this study demonstrate the impact of integrating advanced data augmentation techniques and the EfficientNetV2 model for feature extraction in gastrointestinal (GI) disease detection. By focusing on robust augmentation and an adaptable feature extraction approach, this methodology addresses the variability and complexity present in GI endoscopic images. Notably, this approach attempts to counter issues such as lighting inconsistency, varying angles, and imaging noise, which frequently challenge models trained on medical datasets. Our choice of EfficientNetV2 is validated through its ability to balance depth, width, and resolution effectively, showcasing strong feature extraction capabilities in han- dling diverse GI conditions.

The augmented dataset, particularly with the added classes, provides an enriched platform that is closer to real-world scenarios. This inclusion broadens the model's diagnostic utility, allowing it to better distin- guish between normal and abnormal GI features, as well as between different pathologies. The improved accuracy observed in the results is indicative of the benefits that data diversity and careful class representation can bring to the training process. Moreover, the stacking ensemble methods, which will be part of future phases, aim to complement this initial setup by leveraging the strengths of other models in combination with EfficientNetV2 to further improve detection rates.

While promising, the current setup is not without limitations. Training deep learning models with ex- tensive augmentation can be computationally intensive, potentially limiting the model's deployment in resource- constrained settings. Future work will aim to optimize computational efficiency, perhaps by investigating model compression techniques or adaptive scaling methods. Additionally, as we prepare for real-world clinical appli- cations, interpretability remains a key focus. Transparent diagnostic outputs that clinicians can rely on will be essential to the successful integration of this system into healthcare workflows.

## VII. CONCLUSION

This initial phase of the proposed multi-step approach offers a compelling foundation for enhancing GI disease detection. Through the strategic use of data augmentation and EfficientNetV2-based feature

extraction, the model addresses core challenges in medical imaging, partic- ularly in the context of GI diagnostics. The inclusion of new, clinically relevant classes in the GastroVision dataset not only improves model accuracy but also aligns the model's outputs more closely with clinical needs. This study underscores the importance of combining data diversity with model flexibility, creating a robust system capable of adapting to the intricacies of GI endoscopy images.

Looking ahead, future work will expand upon this foundation by incorporating ensemble methods to syn- thesize outputs from multiple model architectures, ulti- mately aiming for even higher precision and recall in detecting a wide range of GI conditions. The goal is to build a comprehensive, reliable diagnostic tool that can offer substantial support to clinicians, enhancing diagnostic accuracy and contributing to improved patient outcomes. With further refinement, this approach holds promise for creating a scalable, AI-driven diagnostic framework that could be instrumental in the early de- tection and management of GI diseases.

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