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Disease Detection in Gastrointestinal Endoscopic Images Using Deep Learning

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Abstract
The diagnosis of gastrointestinal diseases by endoscopy is very important for early treatment. This work presents an automatic system for characterization of gastrointestinal endoscopic images based on deep learning methods. This system is aimed to discriminate Normal from multiple disease states like Polyps, Ulcerative Colitis, and Esophagitis. Image processing and data augmentation methods are used to improve the model's robustness. Different CNN (convolutional neural network) architectures like VGG16, InceptionV3 and ResNet50 are used and performance analyzed. The trained models can predict disease categories from input endoscopic images. For the performance analysis, standard measures such as accuracy, precision, recall, and F1-score are used to verify the performance of the proposed method. Overall, VGG16 provided a high classification accuracy of 91% compared to other models.
Keywords: *Convolutional Neural Networks; Deep Learning; Gastrointestinal Disease Detection; Gastrointestinal Endoscopic Images; Medical Image Classification.*

1. Introduction
Gastrointestinal diseases are one of the main public health concerns that require early and accurate diagnosis to provide timely prevention, management and treatment (Liu et al., 2023; Kim et al., 2024). Gastrointestinal endoscopy, including colonoscopy, is widely used for diagnosing gastrointestinal diseases; however, manual review of images is time-consuming (Zhang et al., 2025). In the era of increasing use of medical imaging, automated and trustworthy diagnostic methods are critical. This work is concentrated on disease detection on gastrointestinal endoscopy images with deep learning models. To overcome these limitations, this project applies advanced deep learning models for automated disease classification. Advanced models capable of multiclass gastrointestinal disease classification are developed to help doctors in clinical processes. The intended system targets increasing the diagnostic accuracy, decreasing human effort, and ensuring accurate early-stage disease detection in clinical practice.

2. Related Work
The current system utilizes the deep learning model to auto-recognize the multi-centered colorectal polyp images based on colonoscopy and helps in detecting diseases at an early stage. It is based on the pre-trained CNN models to extract visual features and image-wise classification. The system enhances diagnostic aid by minimizing doctors' manual efforts as well as assisting in quicker screening process. An AI model examines texture, shape, and color patterns on colonoscopy images to identify the types of polyps. It enables early detection and planning of the treatment. Many research studies have concentrated on polyp detection and classification with CAD systems based on deep learning algorithms. CNNs, e.g. VGG, ResNet, DenseNet and Inception derivations are extensively studied for colonoscopy image analysis due to their strong feature extraction abilities. Also, object detection models like YOLO have been used for real-time lesion detection with promising accuracy and detection speed.More recent

works have also incorporated attention mechanisms and transformer-based models to enhance feature representation and improve multi-class classification performance. Despite these innovations, most prior methods are focused simply on polyp-only categorization and do not tackle holistic multi-class colorectal disease detection. Some researchers are based on single center or private dataset, impairing their applicability to clinical practice.

3. Problem Statement

Gastrointestinal endoscopy is widely used to diagnose gastrointestinal diseases, but manual identification of endoscopy images is time-consuming, and the diagnosis is subject to clinician experience, resulting in inconsistent findings. Most of these existing AI-based solutions are often disease specific and struggle to be generalized over several diseases since there are differences between patients due to personalization/personal variation from inter-patient as well as class imbalances. Thus, a deep learning approach is needed to develop a system that can automatically classify various types of diseases from endoscopic images. This project aims to develop a multiclass classification system to identify Normal cases, Polyps, Ulcerative Colitis, and Esophagitis, supporting more consistent and efficient disease identification.

4. Proposed Methodology

The proposed system is a smart AI-based disease detection framework for endoscopic images, which also performs multi-class disease classification: Normal, Polyps, Ulcerative Colitis, and Esophagitis. It involves several deep learning models including Inception, VGG16, and ResNet for effective feature extraction and performance comparison. It provides a complete pipeline where data are loaded, preprocessed, augmented, processed through the model, and validation/test set is computed. The system is designed for real-world clinical support and research usage with fewer human errors and enhances the capability to detect small or early-stage disease locations.

5. System Architecture

System architecture is comprised of pipelined stages for automated detection of gastrointestinal diseases in endoscopic images. First, the endoscopic image is input into the system and is preprocessed such as resizing, normalization and noise reduction. The preprocessed image is then inputted at the feature extraction level and gets visual related features extracted by convolutional layers. These features are fed into three deep learning models (InceptionV3, ResNet50, and VGG16) for conducting disease prediction. The trained representations are input into a disease classification system which is adjusted over a labeled disease data set to learn and classify. Lastly, the system outputs a diagnosis result which indicates the recognized class of disease.

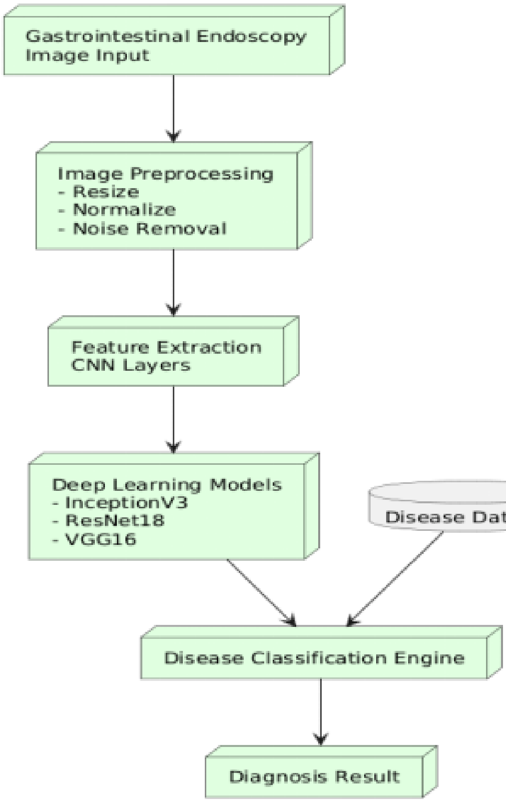

Figure 1 System Architecture of the Proposed System

6. Module Description

6.1.Image Acquisition Module:

This module is for loading the gastrointestinal endoscopic images of the dataset. It ensures that images are saved in a way for further processing to be used.

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6.2.Image Preprocessing Module:

This module performs processing of input images such as resizing, normalization, and denoising. Preprocessing can facilitate deep learning models to learn crucial features better.

6.3.Model Selection and Training Module:

This module contains several deep learning algorithms such as InceptionV3, ResNet50, and VGG16. The models are trained from endoscopic images labeled with disease detection.

6.4.Disease Detection and Classification Module

This software computes endoscopic image processing based on the pre-trained deep learning model. It labels the images as Normal, Polyp, Ulcerative Colitis, and Esophagitis.

6.5.Result Analysis and Visualization Module:

This model performance is tested by accuracy, loss test set precision, recall, and confusion matrix. It also displays the results by graphs for comparison

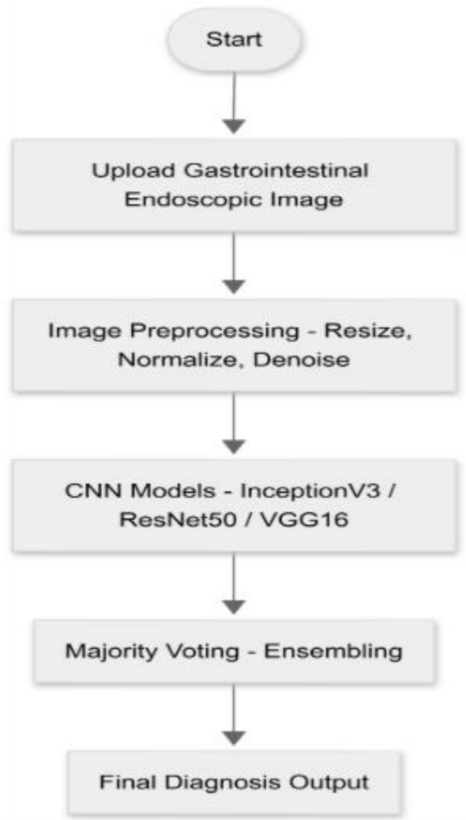

Figure 2 Workflow

7. Workflow

The execution workflow of the proposed disease detection system is shown in Fig. 2. It demonstrates the step-by-step procedure from gastrointestinal endoscopic image input and preprocessing to CNN-based classification, ensemble decision making, and final diagnosis output for precise disease recognition.

8. 8. ALGORITHM DESCRIPTION

This section describes CNN algorithms which are commonly used for automatic disease detection in GI endoscopic images. Three deep learning network architectures, namely InceptionV3, ResNet50 and VGG16, are used for extracting distinctive features and multiclass disease classification.

8.1.A. InceptionV3

In this framework, we use InceptionV3 to capture complex and multi-scale features on gastrointestinal endoscopic images. The pre-processor ImageDataGenerator is used to load the dataset, followed by loading of the InceptionV3 base model without the top-layer. This architecture processes the input image with several parallel convolution filters at multiple scales that assist in capturing fine and coarse disease patterns. The features acquired are then fed into customized fully connected layers for the classification of diseases. The model is compiled and trained on the prepared dataset, followed by validation and evaluation to assess classification performance.

8.2.B. ResNet50

In this framework, we use ResNet50 for disease classification. First, gastrointestinal endoscopic images are collected and preprocessed by resizing and normalization. A pre-trained ResNet50 model is loaded, and the final classification layer is removed. The main concept behind the design of ResNet50 is its residual connections which enable it to learn deep features without suffering from vanishing gradients. Following feature extraction, fully connected layers are used to finetune the model to our medical dataset for better disease classification.

8.3.C. VGG16

In this framework, we use VGG16, which is a very deep 16-layer CNN (13 convolution layers + 3 fully connected layers) and which is particularly useful for

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medical image classification tasks. VGG16 uses a series of small 3×3 convolution filters. The deep layers are able to generate more fine-grained information for the gastrointestinal endoscopic image. There are no shortcuts (somewhat unlike ResNet). The learning is done gradually, layer by layer in sequence order.

9. 9. DATASET DESCRIPTION

The Curated Colon Dataset is a large and high-quality collection of gastrointestinal endoscopic images which have been acquired through the use of Wireless Capsule Endoscopy (WCE) available on Kaggle. The dataset has around 6000 endoscopic images divided into four classes: Normal, Polyps, Ulcerative Colitis, and Esophagitis - with approximately 1500 images in each class. The images are reviewed and annotated by senior gastroenterologists to ensure quality content and clinical significance. The dataset is then split into training, validation, and testing subsets in a systematic way. The deep learning model is trained on the training set; hyper parameters are tuned and performance during training monitored in the validation set. The testing set is used for final evaluation for generalization ability of unseen data.

10. Results and Discussion

10.1. Model Performance

The deep learning models (InceptionV3, ResNet50 and VGG16) were tested on test dataset with four classes [Normal, Polyp, Ulcerative Colitis and Esophagitis] using precision, recall, F1-score and overall accuracy. Finally, the final predicted class was obtained using a majority voting ensemble technique utilizing the class predicted by most of the models. This approach helps improve prediction reliability and increase the chances of obtaining the correct classification.

10.2. InceptionV3

The InceptionV3 model achieved an accuracy of 86%. It achieved a good performance for Normal (F1-score: 0.99) and Esophagitis (F1-score: 0.99) classes. The performance was reduced in Ulcerative Colitis (F1-score: 0.74) and particularly in Polyp (F1-score: 0.59) classes, indicating challenges in distinguishing visually similar classes.

10.3. ResNet50

The ResNet50 model achieved an accuracy of 84%. It achieved a good performance for Normal (F1-score: 0.99) and Esophagitis (F1-score: 0.96) classes. The performance was reduced in Ulcerative Colitis (F1-score: 0.70) and particularly in Polyp (F1-score: 0.69) classes, the model performance was slightly lower than the other two tasks in which subtle differences of inflammatory texture or polyps were hard to capture.

10.4. VGG16

The VGG16 model achieved an accuracy of 91%.It achieved a good performance for Normal (F1-score: 0.98) and Esophagitis (F1-score: 0.98) classes. The performance was reduced in Ulcerative Colitis (F1-score: 0.84) and particularly in Polyp (F1-score: 0.85) classes, suggesting good feature extraction capability and robust multiclass discrimination. VGG16, out of these three models, provided a higher classification accuracy of 91% which is better than compared to the other two models for detecting gastrointestinal disease.

10.5. Ensemble Majority Voting

To improve the robustness of prediction, an ensemble strategy was used by voting predictions of InceptionV3, Resnet50, and VGG16 models. The ensemble model provides a classification accuracy of ~89% showing high robustness and reliability in the classification.

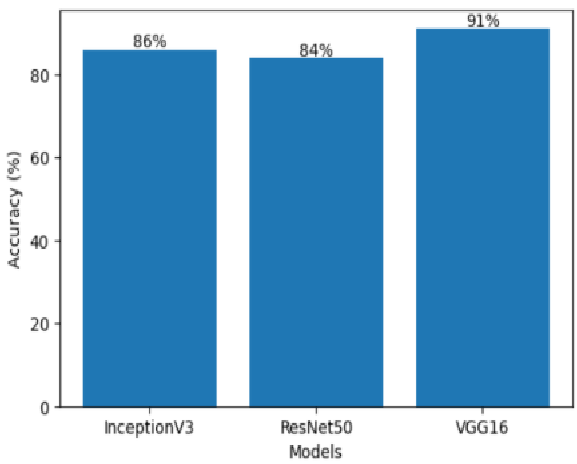

Figure 3 Comparison of Deep Learning Models

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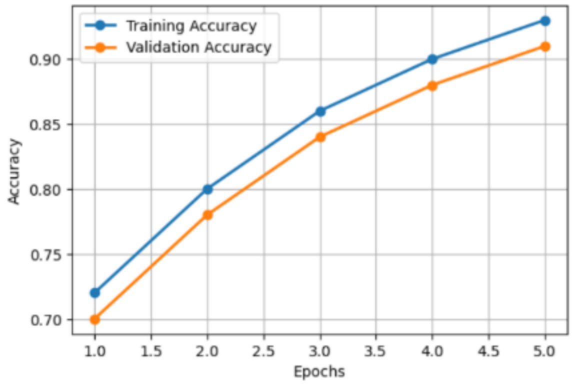

Figure 4 Training and Validation Accuracy Curve

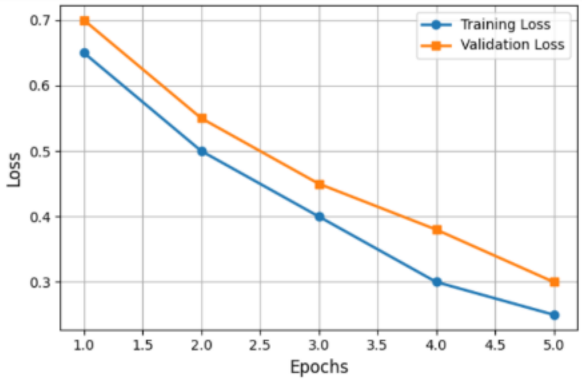

Figure 5 Training and Validation Loss Curve

Conclusion

In this study, a computer-aided system for detecting diseases in gastrointestinal endoscopic images was proposed to help with automatic and accurate GI disease diagnosis. The method employs CNN-based models to learn discriminative representations from gastrointestinal endoscopic images for multiclass disease classification. The system can distinguish between normal and abnormal gastrointestinal conditions with better accuracy and consistency than visual inspection. Experimental evaluations show that the proposed framework can capture meaningful visual patterns from gastrointestinal endoscopic images and enable reliable prediction, this helps in early disease detection and reduces diagnosis variability. This study demonstrates the promise of deep learning algorithms as an assistant technique for computer-aided diagnosis in clinical gastrointestinal endoscopy applications.

Future Work

The disease detection system developed in this study may be improved via retraining and evaluating large and diverse gastrointestinal endoscopic images datasets derived from different clinical centers. The robustness and generalizability of the model would be increased. Further improvements can be achieved by fine-tuning advanced deep learning architectures and hyperparameter tuning. Also, it can be extended to do on-line endoscopic image analysis to assist doctors in routine examinations. Moreover, using visualization techniques focusing on relevant image features leading to predictions can enhance interpretability and a medical trust in our system.

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