

Gastrointestinal Disease Detection Using ConvNext Model

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Abstract: Gastrointestinal (GI) diseases are one of the leading issues of world health care. To minimize potential complications and help to optimize patient outcomes, they must be correctly and promptly diagnosed. However, conventional diagnosis is based on the subjective interpretation of doctors in endoscopic images, and the process is cumbersome, time-consuming and differs among individuals. An automated GI disease classification system using artificial intelligence has been developed from a dataset of 4,000 endoscopic images of Normal Cecum, Polyps, Ulcerative Colitis and Esophagitis. This was to get a more accurate diagnosis. The images were subjected to the usual data preparation and quality improvement procedures prior to the model's creation. Various machine learning and deep learning techniques were explored, including transfer learning techniques and a hybrid classification system based on multiple feature representations for improved disease classification. The model's performance was evaluated using various metrics such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The combination framework achieved the highest overall accuracy of 74.25%, the highest precision score of 73.93%, the highest recall score of 74.25%, the highest F1-Score of 73.65% and the highest ROC-AUC score of 91.59%. The results indicate that the combination of various types of feature representations is helpful to improve the success of automatic gastrointestinal disease classification and facilitate doctors' decision-making.

Index Terms: *Gastrointestinal Disease Classification, Endoscopic Image Analysis, ConvNeXTiny, Feature Fusion, Deep Learning, Computer-Aided Diagnosis (CAD)*”.

1. INTRODUCTION

GI diseases are some of the most common health problems in the world. They are also one of the largest challenges for the healthcare systems, as they are becoming increasingly common and there are a lot of issues with them. It's crucial for physicians to identify polyps, ulcerative colitis, esophagitis, and other gastrointestinal issues early on to help prevent the disease from worsening and to ensure better patient outcomes. One of the most significant diagnostic instruments to study the digestive track is the endoscopic imaging, which allows to view the inside of the body and detect abnormal changes. A growing amount of the medical images are becoming digital. This has created new opportunities for intelligent diagnostic tools that can assist the physician in decision making and in standardizing diagnosis. [1, 2, 3]

Even though medical imaging tools have come a long way, it is still hard to correctly interpret endoscopic images. Traditional diagnostic approaches are often based on the skill and expertise of the physician, and there are subjective interpretations and variations in viewing the same situation, based on different observers. Furthermore, a high number of endoscopy procedures performed in health care facilities contribute to the workload of physicians, and can reduce the quality of diagnosis. Current automated diagnostic solutions

have demonstrated potential, but have encountered difficulties in the ability to generalize, stability across various disease types, and correctly distinguish gastrointestinal diseases with similar appearances [4, 5, 6]. The problems illustrate the key role better computer systems can play in the right and reliable identification of diseases.

The primary objective of this study is to develop an automatic classification system for gastrointestinal diseases based on endoscopic image data by using a smart system. The framework suggested would be designed to aid in the separation of various kinds of GI diseases and to improve the classification of the diseases as well as to improve the accuracy of the diagnosis. Moreover, the approach is designed to leverage extra information that can be gleaned from medical imagery for representation and decision-making. The system is designed to make any clinical health care setting more effective and scalable in its ability to help health care professionals in clinical settings that currently have problems with automated diagnosis [7, 8].

This is a significant addition as it could assist in more accurate, consistent and rapid diagnosis of gastrointestinal disease. Having a computer-aided testing system that can help doctors identify the problem early mean that there will be a lesser chance of misdiagnosing the problem or providing timely medical attention. Such improvements

may mean improved patient care and more streamlined clinical workflows, as well as reduced healthcare expenditures. Also, creating trustworthy intelligent diagnostic frameworks can make it easier for modern healthcare systems to use AI technologies more widely, which will improve the standard and accessibility of medical services [9, 10].

2. LITERATURE REVIEW

In recent years, with the development of artificial intelligence, the computer can quickly and accurately analyze medical images automatically, which greatly helps doctors to diagnose diseases. Zhang et al. proposed that one way to diagnose irritant dermatitis in colorectal cancer patients who have undergone surgery and are wearing a stoma might be through their smartphone photos and a DL framework. This indicates that tools for intelligent diagnosis can be deployed for healthcare real-life applications. Furthermore, they demonstrated the potential of imaging diagnostic methods. The study only examined skin complaints, however, and not other, more common gastrointestinal diseases [11]. Similarly, Ayaz et al. studied CNN models for diagnosing gastrointestinal blockage in children based on X-ray images of the abdomen, and determined they were fairly successful at the task. This approach proved useful for interpreting radiographs, but was only effective in certain situations and types of imaging [12].

A number of studies have looked into more advanced ways to use features to classify images of the digestive system. Sheikh et al. created a multi-model feature fusion framework with explainability methods to make it easier to classify gastrointestinal diseases. The addition of interpretability made clinical transparency easier, but multiple representations could make it more cumbersome to use computers [13]. It was developed by Aadiwal et al. using the global contextual information to develop an ensemble DL approach to detect gastrointestinal lesions. This helped in improving lesion classification and localization. But variability in lesions and the relatively heterogeneous nature of the images remained to be problematic, limiting stability [14]. Abdullah et al. suggested a hybrid collaborative multi-branch design for classifying gastrointestinal diseases. This demonstrates the virtues of having various types of information sources that complement each other. Despite the improvement in classification skills, scaling and generalization to other datasets remained important considerations [15].

There has been a considerable emphasis on hybrid diagnostic frameworks for related gastrointestinal and cancer detection applications as well. Divyavarshini and Rajkumar have devised an improved combination approach to the identification and classification of colon cancer. They stated that it was more precise than other methods. However, the study was mostly about colon cancer and not

about other types of stomach diseases [16]. To develop a DL model capable of automated discovery of anatomical spots in UG tract during endoscopy exams, Roser et al. have created the model. Although the primary goal was not to classify diseases, their results demonstrated the importance of applying computer knowledge of anatomy. Their results demonstrated the importance of computer knowledge of anatomy although the primary goal was not the classification of diseases. Gong et al. proposed a computer-aided diagnosis method for chronic gastritis diagnosis, which adopted a special neural network with good image feature extraction ability. Although the framework had some positive impacts, it was applicable to just a single gastrointestinal condition [18].

Recently, Mirzaei et al. compared different deep learning models for detecting helminth infections. They demonstrated the significance of the model selection for obtaining correct classification of medical images. The study demonstrated that the performance varies between the different designs, so there is no one design that will always perform the best for all the diagnostic tasks [19]. Similarly, Kehkashan et al. explored the application of transformer-based medical imaging solutions for identification of gastroenterological diseases and demonstrated the potential of adopting these technologies for making healthcare systems more sustainable. Although significant progress has been made in prediction accuracy, challenges remain such as the various disease types, similarity in appearance between classes and correct multi-class separation [20].

All these endeavors reflect large strides in smart gastroenterology diagnosis. However, there are still issues with generalisation, multi-disease classification and accurate differentiation between diseases that resemble each other in appearance that need to be addressed. Such imbalances gave rise to the development of a detailed classification which can improve the accuracy with which GI disorders are diagnosed and help clinicians to make meaningful clinical decisions in a variety of GI disorders.

3. MATERIALS AND METHODS

The suggested system is meant to automatically sort endoscopic images into groups of gastrointestinal diseases, which will help doctors make more accurate and faster diagnoses. The system has been constructed and evaluated with a set of 4,000 annotated endoscopy images, which included Normal Cecum, Polyps, Ulcerative Colitis and Esophagitis images. The overall process involves data collection, data quality enhancement, feature representation, model training, and performance evaluation. The framework integrates deep visual representations extracted by transfer learning with handcrafted medical features important to the topic that capture features of gastrointestinal tissues clinically relevant to diagnosis, with the aim of improving diagnosis. This is a fusion feature processing technique which allows the model to use not just

general meaning information but also disease specific visual patterns. This helps to differentiate the various disease entities. The framework of classification is further refined for increased reliability, strength and generalization to other image examples. The experiment results prove that combined method is effective in detecting different gastrointestinal diseases, and it is more reliable to make computer-aided diagnostic decisions in clinical application.



“Fig.1 Proposed Architecture”

The proposed classification of gastrointestinal diseases is proposed to be a mixture of deep learning and manually performed feature analysis. The first step of the endoscopic images is resizing, normalizing, noise reduction, feature extraction, visualization, and partition in various parts. High-level deep visual features are extracted by ConvNeXtTiny, and handcrafted medical features extract image features that are clinically important. Both the sets of features are fused together to form a complete picture in a feature fusion layer. The combined features are fed into a dense classification network and a Softmax layer does the multi-class classification. This results in a better diagnostic accuracy and classification performance for Normal Cecum, Polyps, Ulcerative Colitis and Esophagitis.

a) Dataset Collection:

These data were collected from a publicly available medical image repository with endoscopic images annotated as gastrointestinal diseases. It contains 4000 pictures from 4 categories: Normal Cecum, Polyps, Ulcerative Colitis, and Esophagitis. There are the same number of examples for each group. High-resolution endoscopic images of various gastrointestinal diseases and visual characteristics. It has a balanced class distribution, which means that it is ideal to be used in jobs that require sorting into more than one class, in the training of the model and tests, because it reduces bias from the model. The number of images or disease groups is sufficient to ensure reliable performance evaluation and to develop robust computer-aided diagnostic systems that are useful in the clinical world.

b) Pre-Processing:

The model was developed by applying a full preprocessing pipeline to enhance the data quality, extract meaningful information, and ensure the evaluation's accuracy. The

result are more consistent datasets, more accurate features, more stable model and, overall, better performances in the classification of things to obtain gastrointestinal diseases.

Image Resizing: All of the endoscopic pictures were resized so that they all had the same spatial resolution of 160 × 160 pixels. By making the dimensions of pictures uniform, the dataset is consistent and will help to accelerate processing during the training and testing of the model. This reduces the workload on the computer and the required memory, and will maintain the key visual components required to diagnose disease. Secondly, it is easier to get accurate feature extraction and the changes that occur due to different picture capturing settings are minimum if one uses the same image size. This will result in a more stable model and better overall learning.

Image Normalization: Picture normalization and noise reduction were adopted to enhance the quality of the images and the visual information consistency among the dataset. The values of pixel intensities were all set to the same scale. This made it possible for the model to settle steadily and made it less sensitive to changes in lighting. Also, some techniques to smooth were applied to eliminate unwanted noise and small artifacts which often appear in endoscopic images. Such enhancements are more convenient for better visualization of critical anatomical structures and diseased areas. This allows the classification system to concentrate on patterns and features that aid in diagnosis.

Feature Extraction: The clinically useful information extracted from the endoscopic pictures was obtained by a process called "feature engineering". Several descriptive features such as edge, brightness level, color distribution and inflammation were removed to be able to show disease-specific visual patterns. These human-made medical features complement image-based representations, as they provide further medical subject knowledge which may not be captured by automated learning completely. The last group of features enhances the diagnostic framework's classification and makes it more easy to distinguish between diseases, with increased accuracy, stability, and readability.

Visualization: Exploratory data analysis was done to learn more about the characteristics of the dataset and to see how the disease groups and extracted features were spread out. Using various visualization methods, the class balance, feature relationships, image quality and data variability were examined. This procedure can be used to identify potential errors, bias, and unusual aspects that could impact the model's accuracy. Exploratory analysis can be used to make more informed decisions and increase the reliability and usefulness of the classification system, by determining the basic data structure before a model is developed.

c) Training and Testing:

To ensure that the evaluation process was fair and reliable the data set was divided into multiple training, validation and testing subsets. The training subset was provided to develop knowledge of the patterns of the disease and the validation subset was provided to monitor success and improve the model. Only the test subset was used for the final test of the results. This is a structured partitioning approach that reduces the danger of overfitting, provides an objective means to compare models, and provides some insight into the ability of the framework to generalize to images of the digestive system that it has not seen before.

d) Algorithms:

ConvNeXtTiny Deep Feature Extraction: The deep features extracted by ConvNeXtTiny were then fed into four additional parts, which further enhanced the classification accuracy. Handmade Medical Features were added to provide scientifically useful information regarding the features of tissues and visual patterns that are specific to diseases. These features were fused together with ConvNeXtTiny representations using a Feature Fusion Layer. This allowed the model to leverage information from learned features and topic-specific features. A Dense Classification Network was then run on the combined image and trained to find complex relationships between the features that were removed. Finally, a Softmax Classification Layer classified the disease class probabilities and categorized each picture into one of four disease groups. This was helpful in making the classification process more accurate, reliable, and robust.

Accuracy: The accuracy of a test is how well it is able to differentiate between healthy and sick individuals. To understand how accurate a test is, let's estimate the percentage of positive and negative results. For math, it is represented as

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Precision: Precision is the percentage of correctly classified cases or samples to that which were correctly classified as positive. Therefore, here's the way to calculate the precision:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

Recall: In ML, recall is a metric that shows how well a model can find all the important instances of a certain class. It represents the ability of the model to represent examples of a class. It is determined by the ratio of the number of positive observations that are predicted correctly, to the number of all positive observations.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1-Score: The F1 score is a metric to evaluate the accuracy of a ML model. Adds together the accuracy and the recall scores of a model. This measure of accuracy will be the number of times the model was correct for the entire data set.

$$F1\ Score = 2 * \frac{Recall * Precision}{Recall + Precision} * 100 \quad (1)$$

4. EXPERIMENTAL RESULTS

Table.1 Performance Evaluation Table

Metric	Score
Accuracy	74.25%
Precision	73.93%
Recall	74.25%
F1 Score	73.65%
ROC-AUC	91.59%

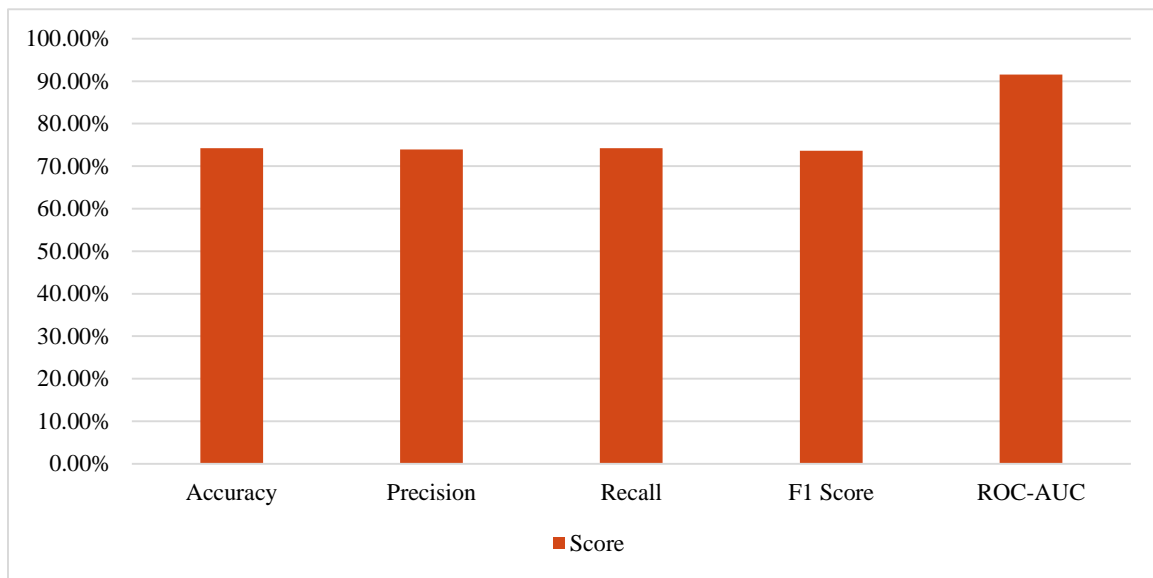
The performance of the gastrointestinal disease classification framework in general is presented in Table 1. Results indicate that 74.25% of cases are correctly predicted by the model and it has a very high ROC-AUC of 91.59%. This means it can effectively distinguish between different gut diseases and also provide accurate diagnosis for a wide variety of gut diseases.

Table.2 Performance Evaluation Table

Class	Precision	Recall	F1-Score
Normal Cecum	0.95	1.00	0.98
Polyps	0.69	0.84	0.76
Ulcerative Colitis	0.60	0.58	0.59
Esophagitis	0.71	0.55	0.62

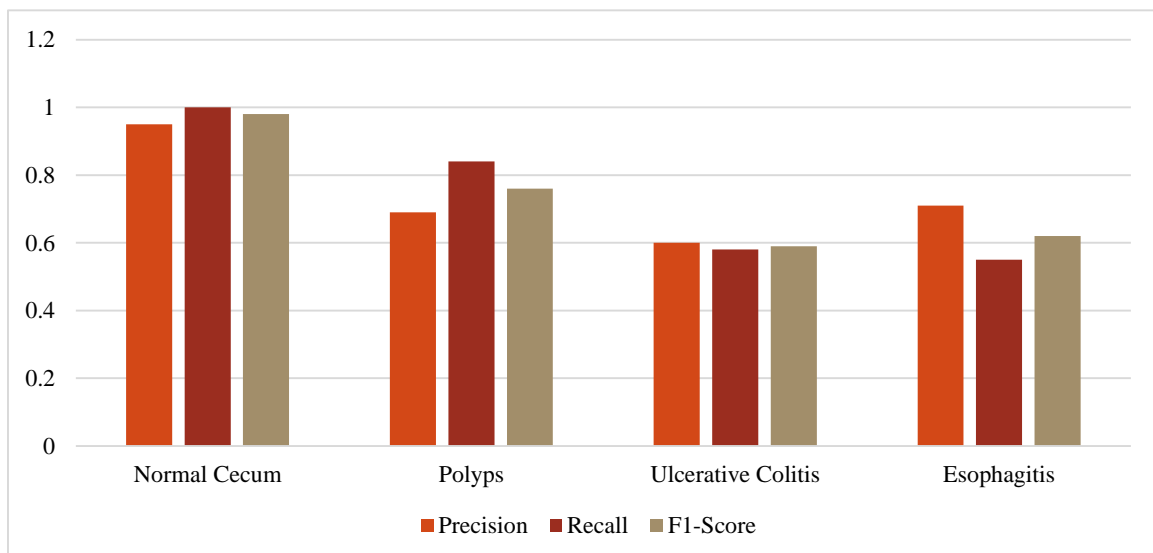
The results of the performance evaluations for each class are shown in Table 2. The Normal Cecum had the best sorting performance and the Polyps had the average sorting performance. In contrast, Ulcerative Colitis and Esophagitis were given lower marks, indicating that the disease categories were not easily distinguished and were similar.

Graph.1 Comparison Graph



In Graph 1, you can see how the gastrointestinal disease classification system did on different evaluation criteria. All of the accuracy, precision, recall and f1-score were consistent. The ROC-AUC was the highest, indicating that the model was able to distinguish the two classes with good accuracy and was a good diagnostic tool.

Graph.2 Comparison Graph



As can be seen from the Graph 2, Precision, Recall and F1-Score are compared for each class of gut diseases. Normal Cecum came off best, and Ulcerative Colitis and Esophagitis came off much worse, so it was more difficult to group them and there was more similarity between the groups.

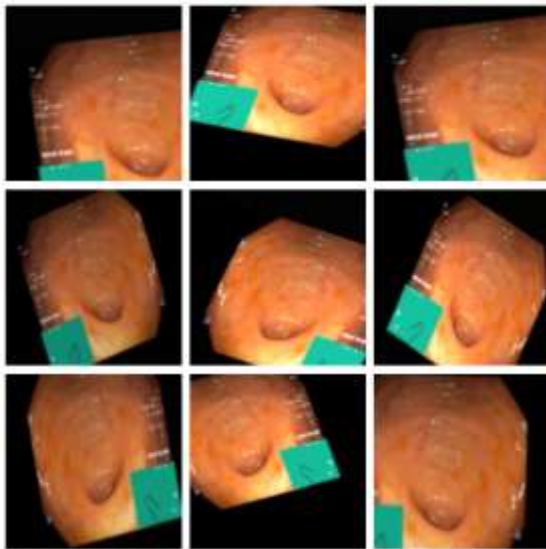


Fig.2 Average Texture Roughness



Fig. 3 Predicted Disease

5. CONCLUSION

Last, the primary objective of such a scheme was to develop an intelligent and reliable end-endoscopic image analysis automatic classification system for gastrointestinal diseases. This would assist doctors in making accurate diagnoses and timely. For this purpose, 4,000 annotated endoscopic images from four categories of gastrointestinal diseases (Normal Cecum, Polyps, Ulcerative Colitis and Esophagitis) were utilized. The framework developed incorporated DL-based visual representation learning as well as handcrafted features that were clinically relevant to obtain additional diagnostic information from medical images. A hybrid classification approach was used to enhance the distinction between diseases and to predict within different disease classes. Standard classification measures were used to do a full set of experiments that

proved how well the framework worked. The success rate of the proposed method was 74.25% overall, which indicates that it was able to correctly differentiate between various digestive diseases. The other important contribution was the addition of deep and handcrafted feature models, which stabilized the system and enabled to obtain more precise classification results. The developed system contributes to the advancement of computer-aided gastrointestinal diagnosis by providing a fast and reliable, and automated decision making process. This is demonstrated by its ability to assist doctors in diagnosing disease; reduce diagnostic error; and enhance clinical efficiency.

Future work could include enhancing the dataset with additional and/or varied types of GI images, so that the model would be more general and the accuracy of the diagnostics would increase. The framework may be expanded by adding additional gastrointestinal diseases and types of lesions for additional clinical applications. Using AI methods that can be explained might make things clearer and boost clinician trust in automated predictions. Real-time deployment in endoscopic systems and integration with hospital decision-support tools can also improve the efficiency of clinical workflow, making it possible to make diagnoses more quickly and with more confidence in real-life healthcare settings.

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