RAJALAKSHMI
ENGINEERING COLLEGE
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AI BASED GASTROINTESTINAL DISEASE DIAGNOSIS USING NLP

Submitted by

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ABSTRACT

Gastrointestinal (GI) diseases represent a major global health burden, and early, accurate diagnosis is essential for reducing complications and improving patient outcomes. Conventional diagnostic approaches, particularly those involving endoscopic image interpretation, are often time-intensive and heavily reliant on specialized clinical expertise. To overcome these limitations, this project presents an AI-driven diagnostic framework that combines deep learning and natural language processing (NLP) to streamline and automate the detection and reporting of GI disorders. The system begins with image preprocessing, where input endoscopic images are resized to 224×224 pixels and normalized to ensure consistency. These images are then analyzed using a fine-tuned DenseNet121 model, which has been pretrained on large-scale datasets and adapted through transfer learning for the classification of various GI conditions, including polyps, ulcers, and inflammation. Performance evaluation shows the model achieves an overall accuracy of 82%, with strong F1-scores across multiple classes—such as 0.93 for normal-pylorus, 0.85 for ulcerative-colitis, and 0.85 for normal-cecum—indicating robust classification capability. Following prediction, the identified class label is passed into an NLP-based report generation module, which uses a transformer architecture to produce a coherent and medically relevant diagnostic summary. This text can then be translated into different regional languages and converted to speech, supporting accessibility for patients with sensory or language impairments. By uniting image-based AI with contextual text generation, the system offers a scalable, explainable, and accessible solution that improves clinical workflow efficiency and supports informed, timely decision-making in GI healthcare.

Keywords: Deep learning, DenseNet121, Medical image classification, Natural language processing, Medical report generation, Transfer learning, Accessibility.

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CHAPTER 1

INTRODUCTION

Gastrointestinal (GI) diseases are among the most prevalent health issues globally, affecting millions of individuals each year. These disorders can range from mild discomfort to life-threatening conditions such as colorectal cancer. Accurate and early diagnosis of GI conditions plays a pivotal role in preventing complications and ensuring effective treatment. However, traditional diagnostic methods, such as manual analysis of endoscopic images by medical professionals, are time-consuming, subjective, and require extensive expertise. This dependency on human interpretation not only limits diagnostic scalability but also increases the chances of oversight or misclassification, especially in high-pressure clinical environments.

With the advancement of Artificial Intelligence (AI), particularly in the domains of deep learning and natural language processing (NLP), there is a growing opportunity to automate and enhance various aspects of medical diagnostics. In the field of gastroenterology, AI can support doctors by quickly and accurately identifying abnormalities in endoscopic images and generating interpretable medical reports, thereby reducing the diagnostic burden and supporting clinical decision-making. Deep learning models, especially convolutional neural networks (CNNs) such as DenseNet121, have shown exceptional performance in visual recognition tasks, making them highly effective for medical image classification.

In addition to image analysis, natural language processing adds another critical layer of intelligence to the system. Once the image has been classified, NLP techniques can be employed to automatically generate human-readable reports based on the identified disease. This integration bridges the gap between technical diagnosis and patient communication, ensuring that results are not only accurate but also accessible to both healthcare providers and patients.

The proposed system combines these technologies into a unified diagnostic pipeline. Starting with image preprocessing for standardization, the system then uses DenseNet121 for disease classification, followed by an NLP-based text generation model for report creation. Furthermore, the final output can be translated into regional languages and converted into speech to support visually impaired or linguistically diverse patients. The overall goal of this project is to create a scalable, efficient, and inclusive diagnostic assistant that improves the speed and quality of gastrointestinal disease detection while ensuring accessibility and explainability in real-world clinical settings.

This intelligent system is particularly relevant in the context of increasing patient loads and limited availability of specialized doctors, especially in rural and underdeveloped regions. By leveraging AI-based automation, the proposed approach not only accelerates the diagnostic process but also ensures consistency in results. Ultimately, the solution aims to democratize access to high-quality healthcare by integrating cutting-edge machine learning techniques into practical, patient-centered applications.

CHAPTER 2

LITERATURE REVIEW

[1] Title: An In-Depth Study of Personalized Anesthesia Management Models in Gastrointestinal Endoscopy Based on Multimodal Deep Learning

Authors: Hanqi Shi, Hongyu Wang, Xibing Ding, Zheng Dang (2025)

This study introduces a personalized anesthesia model using multimodal deep learning to enhance GI endoscopy outcomes. It integrates LSTM, geometric manifold optimization, and sparse matrix classifiers to predict anesthesia states with real-time patient data. The proposed system achieved an F1-score of 0.711, showing improved prediction accuracy. It adapts to varying patient responses and aims to personalize sedation levels. This approach demonstrates significant potential in clinical settings. However, limitations include a small sample size and restricted clinical generalizability. Future work may focus on larger datasets and broader trials.

[2] Title: AI in Endoscopic Gastrointestinal Diagnosis: A Systematic Review of Deep Learning and Machine Learning Techniques

Authors: Jovita Relasha Lewis, Sameena Pathan, Preetham Kumar (2024)

This review evaluates AI methods used for diagnosing gastrointestinal diseases with a focus on endoscopic imaging. It explores both deep learning (DL) and machine learning (ML) approaches, particularly for detecting conditions like cancer and colon polyps. Convolutional Neural Networks (CNNs) were found to be the most effective and widely used. The study provides a useful framework for researchers aiming to improve diagnostic tools. It also highlights limitations such as poor dataset quality and lack of large-scale clinical validation. The review emphasizes the need for robust, annotated datasets and clinical trials.

[3] Title: Gastrointestinal Disease Classification Using Hierarchical Spatio Pyramid TranfoNet With PitTree Fusion and Efficient-CondConv SwishNet

Authors: V. Sharmila; S. Geetha (2024)

This paper proposes a new model, Hierarchical Spatio Pyramid TranfoNet, for improved classification of gastrointestinal diseases. It uses Spatial Transformer Networks with spatial pyramid pooling for detailed image analysis. The PitTree Fusion technique helps differentiate between normal and dyed tissues in endoscopic images. Additionally, Efficient-CondConv SwishNet enhances feature extraction efficiency. The model achieved 98.2% accuracy on the Kvasir dataset. While effective, it heavily relies on high-quality data. Generalization to diverse clinical settings remains a challenge.

[4] Title: Gastrointestinal Tract Disease Classification Using Residual-Inception Transformer With Wireless Capsule Endoscopy Images Segmentation

Authors: Erdal Özbay (2024)

This study introduces a deep learning model for colorectal cancer diagnosis using WCE images. The method segments GI regions using a transformer-based model with split token embedding and cross-channel feature learning. It integrates Residual and Inception blocks for efficient feature representation. Evaluated on the WCECCD dataset, the model achieved 99.50% accuracy. This performance exceeds existing state-of-the-art methods. The study highlights the model's potential in improving early GI disease detection. Clinical applicability, however, may depend on imaging hardware and data consistency.

[5] Title: Improving Endoscopic Image Analysis: Attention Mechanism Integration in Grid Search Fine-Tuned Transfer Learning Model for Multi-Class Gastrointestinal Disease Classification

Authors: Mohamed A. Elmagzoub, Swapandeep Kaur, Sheifali Gupta (2024)

This study proposes a transfer learning approach using a fine-tuned ResNet101 model with attention mechanisms. It classifies eight gastrointestinal diseases using endoscopic of images from the Kvasir dataset. Attention layers help the model focus on critical diagnostic regions, boosting performance. The model achieved 93.5% accuracy, outperforming standard transfer learning methods. Grid search was used for fine-tuning hyperparameters. Despite high accuracy, limitations include a relatively small dataset. Overfitting remains a concern for future deployment.

[6] Title: An Efficient Optimal CapsNet Model-Based Computer-Aided Diagnosis for Gastrointestinal Cancer Classification

Authors: Fahdah A. Almarshad, Prasanalakshmi Balaji, Liyakathunisa Syed (2024)

This paper introduces the SOADL-GCC model, a CapsNet-based diagnosis system for GI cancer. It uses the snake optimization algorithm for hyperparameter tuning and bilateral filtering for preprocessing. A Deep Belief Network is employed for final classification. The model integrates image enhancement, feature extraction, and optimized learning. On the Kvasir dataset, it achieved a remarkable 99.72% accuracy. Limitations include reliance on a single dataset. It lacks validation through clinical trials, adaptability.

[7] Title: Computer Aided Diagnosis for Gastrointestinal Cancer Classification Using Hybrid Rice Optimization With Deep Learning

Authors: Olfat M. Mirza, Aisha Alsobhi, Tawfiq Hasanin, Mohamad Khairi Ishak (2023)

This study presents the GDDC-HRODL model for classifying GI cancers using a combination of deep learning and hybrid optimization. It utilizes CNN-based feature extraction, HybridNet, and an attention-based LSTM. Hyperparameter tuning is performed using Hybrid Rice Optimization (HRO) and Ant Lion Optimization (ALO) algorithms. The model effectively distinguishes between benign and malignant images. The methodology improves diagnostic accuracy through advanced image analysis. However, it requires extensive preprocessing. Optimization complexity may hinder real-time application.

[8] Title: Endoscopic Image Analysis for Gastrointestinal Tract Disease Diagnosis Using Nature Inspired Algorithm With Deep Learning Approach

Authors: Abdulrahman Alruban, Eatedal Alabdulkreem, Majdy M. Eltahir (2023)

The EIAGTD-NIADL technique integrates deep learning with a nature-inspired optimization method for diagnosing GI diseases. It applies bilateral filtering for preprocessing and uses an improved ShuffleNet for efficient feature extraction. An Improved Spotted Hyena Optimizer (ISHO) enhances model performance. A stacked LSTM performs the final classification. This method delivers high accuracy on benchmark datasets. However, the system's complexity and dependency on optimization.

[9] Title: Computer-Aided Gastrointestinal Diseases Analysis From Wireless Capsule Endoscopy: A Framework of Best Features Selection

Authors: Muhammad Attique Khan, Seifedine Kadry, Majed Alhaisoni (2020)

This paper proposes a fully automated system for identifying stomach infections such as ulcers using WCE images. A retrained VGG16 model and saliency-based detection are used for feature extraction. The best features are selected through Particle Swarm Optimization (PSO). Final classification is done using a Cubic SVM classifier. The system achieved 98.4% accuracy, surpassing existing methods. However, it relies on a private dataset, limiting transparency. Scalability to varied datasets remains uncertain.

[10] Title: Review on the Applications of Deep Learning in the Analysis of Gastrointestinal Endoscopy Images

Authors: Wenju Du, Nini Rao, Dingyun Liu (2019)

This review focuses on deep learning, especially CNNs, for analyzing GI endoscopy images. It covers use cases like disease detection, classification, segmentation, and image recognition. The paper also explores technical challenges such as limited datasets and generalization issues. It highlights the growing role of AI in medical diagnostics. The review concludes with suggestions for future research and clinical integration. It provides a solid foundation for newcomers in medical image analysis using DL.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 HARDWARE REQUIREMENTS:

- CPU: Intel Core i5 (minimum) or equivalent
- GPU: Integrated Graphics (Dedicated GPU recommended for better performance)
- Hard Disk: Minimum 40 GB of free storage
- RAM: 8 GB (16 GB recommended for optimal performance)

3.2 SOFTWARE REQUIRED:

- **Development Environments:**
  - Google Colab
  - Jupyter Notebook (version 6.0 or later)

- **Libraries and Frameworks:**
  - TensorFlow (version 2.12 or later)
  - Keras (included with TensorFlow 2.x)
  - NumPy (version 1.18 or later)
  - Matplotlib (version 3.3 or later)
  - Seaborn (version 0.11 or later)
  - Scikit-learn (version 0.24 or later)

- **Web Application & Deployment Tools:**
  - Streamlit (version 1.20 or later)
  - Pyngrok (version 5.0 or later)

- **NLP Integration:**
  - Transformers (small - T5 model)

CHAPTER 4

SYSTEM OVERVIEW

4.1 EXISTING SYSTEM

Existing systems for gastrointestinal disease diagnosis using deep learning methods have demonstrated significant advancements but also face various challenges. Automated systems leverage deep learning architectures like CNNs, LSTMs, and hybrid models for classifying endoscopic images and detecting conditions such as colorectal cancer, ulcers, and polyps. For example, Shi et al. (2025) introduced a personalized anesthesia model using multimodal deep learning, achieving a notable F1-score of 0.711, though the model faced limitations due to sample size and clinical applicability. Özbay (2024) proposed a transformer-based model for wireless capsule endoscopy, which achieved 99.5% accuracy, but its reliance on high-quality datasets presents challenges for generalization. Other studies, such as Elmagzoub et al. (2024), implemented attention mechanisms with ResNet101, achieving 93.5% accuracy, but faced overfitting risks with small datasets. Furthermore, Almarshad et al. (2024) utilized CapsNet for cancer classification, achieving an impressive 99.72% accuracy but highlighted the need for larger clinical trials to validate its real-world effectiveness. Despite their promising results, many systems in this field are hindered by dataset quality, limited clinical validation, and computational demands, underscoring the need for scalable, generalizable models in gastrointestinal disease detection.

4.1.1 DRAWBACKS OF EXISTING SYSTEM

Existing systems for gastrointestinal disease diagnosis using deep learning face several significant drawbacks. Manual methods for diagnosis, such as expert interpretation of endoscopic images, are time-consuming, prone to human error, and unsuitable for real-time applications due to their reliance on specialist expertise. Automated systems, while addressing some of these challenges, still encounter limitations. Deep learning models, such as CNN-based classifiers, often struggle with generalization to diverse datasets and may not effectively handle regional variations in gastrointestinal conditions. Models like the one by Özbay (2024) that rely on wireless capsule endoscopy scans require high-quality data for optimal performance, limiting their applicability in real-world, less-controlled environments. Advanced methods, such as those integrating attention mechanisms or transformers, tend to demand substantial computational resources, making them unsuitable for deployment in resource-constrained settings. Additionally, some models are prone to overfitting when trained on limited datasets, reducing their robustness and scalability. Despite achieving high accuracy, many systems face challenges in clinical validation and real-time application, underlining the need for more efficient, scalable, and clinically viable solutions.

4.2 PROPOSED SYSTEM

The proposed system aims to develop a real-time, AI-powered solution for the detection and diagnosis of gastrointestinal diseases through endoscopic images. By leveraging advanced deep learning techniques, the system automatically analyzes endoscopic images to classify various GI conditions, such as polyps, ulcers, and cancer, offering an accurate and scalable alternative to manual diagnosis. The system employs a combination of Convolutional Neural Networks (CNNs) and transformer-based models for feature extraction and classification, ensuring high precision in identifying abnormalities in endoscopic images.

For medical report generation, the system integrates Natural Language Processing (NLP) techniques, specifically a T5-small model, to automatically generate detailed medical reports based on the detected conditions. This ensures that clinicians receive clear, concise, and contextually relevant information to aid in decision-making. The system’s real-time processing capabilities make it suitable for deployment in clinical settings, enhancing the efficiency of diagnosis and improving workflow.

Designed for accessibility and ease of use, the system operates on standard computing hardware, removing the need for specialized equipment. By automating the process of disease detection and report generation, the system significantly reduces diagnostic time and human error, providing a reliable tool for healthcare professionals. Through the integration of deep learning and NLP, the system aims to enhance diagnostic accuracy, streamline clinical workflows, and ultimately improve patient outcomes in gastrointestinal healthcare.

4.2.1 ADVANTAGES OF PROPOSED SYSTEM

- The system enhances the detection and diagnosis of gastrointestinal diseases using advanced deep learning techniques.
- It improves diagnostic accuracy by precisely classifying GI conditions such as polyps, ulcers, and cancer.
- Integration of Natural Language Processing (NLP) allows for automated medical report generation, offering contextually relevant insights for healthcare professionals.
- Real-time processing enables rapid analysis of endoscopic images, suitable for fast-paced clinical environments like hospitals and diagnostic centers.
- The system runs on standard computing hardware, eliminating the need for specialized equipment and ensuring broader accessibility.
- A scalable architecture allows for future updates, including better classification accuracy and support for new disease types.
- It enhances diagnostic workflows, minimizes human error, and provides a cost-effective, reliable solution for GI healthcare.

CHAPTER 5

SYSTEM IMPLEMENTATION

5.1 SYSTEM ARCHITECTURE

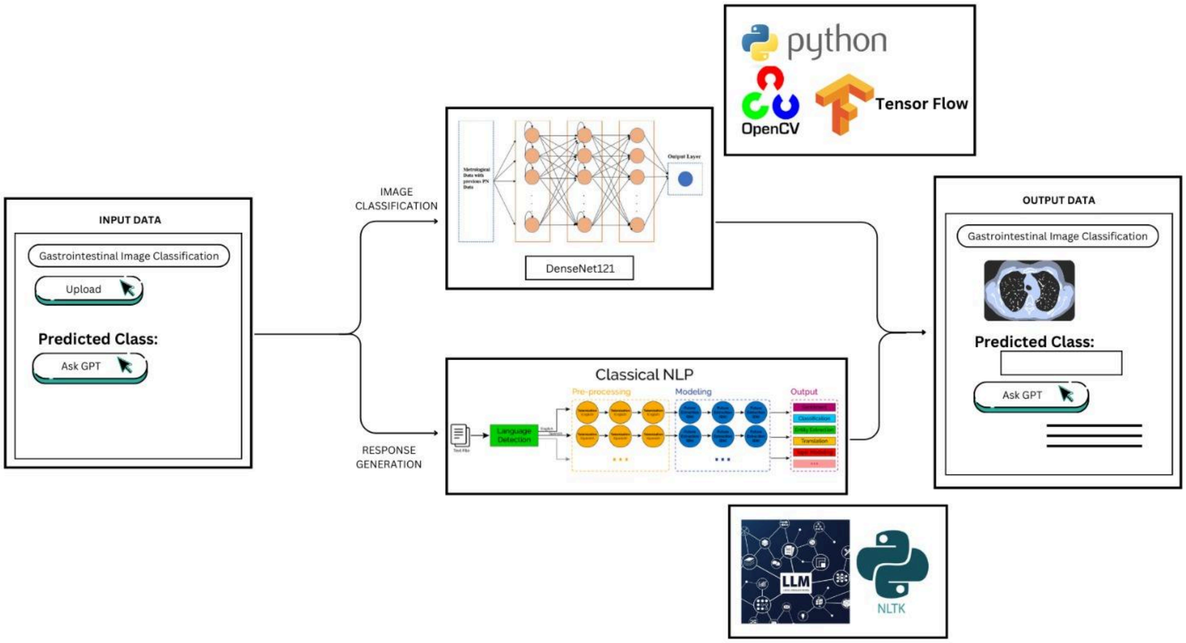


Fig 5.1 *Architecture diagram of AI based Gastrointestinal Disease Diagnosis using NLP*

In figure 5.1, the system architecture for the proposed solution follows a structured pipeline to automate the diagnosis and reporting process using deep learning and natural language processing. It begins with the input image, typically obtained from endoscopic examinations, in formats such as .jpg, .png, or .dcm. These images are first passed through a preprocessing stage, where they are resized to a standard resolution of 224×224 pixels, normalized to a pixel value range between 0 and 1, and optionally augmented. This step ensures uniformity and quality of input using tools like OpenCV and NumPy.

Following preprocessing, the images are forwarded to the image classification module, where a DenseNet121 model, fine-tuned using transfer learning from ImageNet, is used to categorize the image into medical classes such as “Polyp”, “Normal”, or “Ulcer”. This is implemented using the TensorFlow/Keras framework. The resulting class label is then used as input to the text generation (NLP) stage, which utilizes the T5-small model from Transformers library. This model generates a coherent and clinically relevant medical report based on the classification result. Finally, the system produces the final output, displaying both the predicted class label and the generated medical report for integration into patient records or clinical workflows.

5.2 SYSTEM FLOW

The system starts by accepting an input image, which undergoes preprocessing where it is resized to 224x224 pixels and its pixel values are normalized using tools like OpenCV and NumPy. This ensures that the image is in the correct format for the subsequent analysis. The preprocessed image is then passed through a pre-trained DenseNet121 model, leveraging transfer learning to classify the image. This model outputs a class label, such as "Polyp," indicating the presence of a specific medical condition or object in the image. After classification, the system uses the class label to generate a medical report, which describes the identified object or condition in detail. The final output consists of both the class label and the generated medical report, providing a complete and informative result. This approach allows for automated diagnosis or reporting based on image data, enhancing efficiency in medical settings.

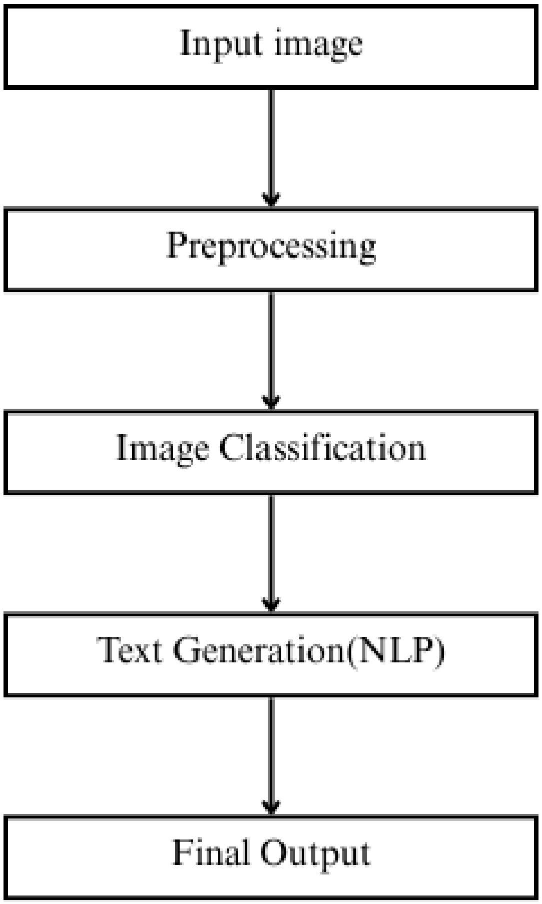


Fig 5.2 *System flow of AI based Gastrointestinal Disease Diagnosis using NLP*

5.3 LIST OF MODULES

- Input Image Handling Module
- Image Preprocessing Module
- Image Classification Module
- Medical Report Generation Module
- Output Display Module

5.4 MODULE DESCRIPTION

5.4.1 INPUT IMAGE HANDLING MODULE

The Input Image Handling Module is responsible for managing the initial stage of the process, where the system receives and organizes the input image data. This module ensures that the medical image, such as an endoscopic scan or CT scan, is correctly uploaded into the system. It handles various image formats, ensuring compatibility and converting them into a standardized form if necessary. The module's role is to provide the subsequent processing modules with correctly formatted image data, allowing for efficient analysis and classification in later stages of the system.

5.4.2 IMAGE PROCESSING MODULE

The Image Preprocessing Module prepares the input image for classification by transforming it into an appropriate format for model analysis. This includes resizing the image to a standard 224x224 resolution, ensuring that it fits the input requirements of the DenseNet121 classification model. Additionally, the module normalizes pixel values, typically scaling them between 0 and 1, which enhances the model's ability to learn and make predictions accurately. The preprocessing ensures that the image data is consistent and ready for further processing in the classification phase, thereby improving the model's performance and efficiency.

5.4.3 IMAGE CLASSIFICATION MODULE

The Image Classification Module is responsible for using a pre-trained DenseNet121 model to classify the input image. The module leverages transfer learning, where the model, trained on large datasets, predicts the presence of specific objects or conditions, such as "Polyp" in the case of medical imaging. It outputs a class label based on the features identified in the image. The classification module serves as the core of the system, enabling accurate recognition and categorization of the object, which is essential for generating the subsequent medical report. The accuracy and reliability of this module are critical for the overall system's success.

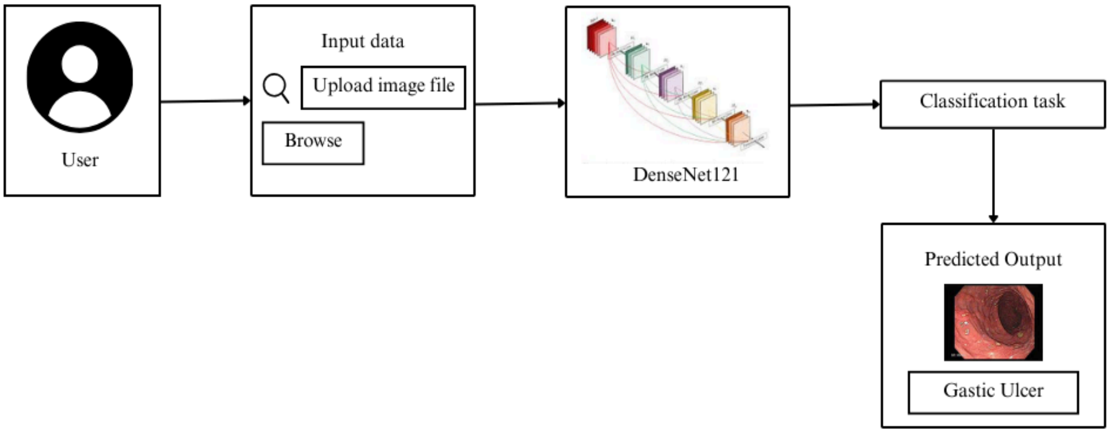


Fig 5.4.3 *Image Classification Module Architecture Diagram*

5.4.4 MEDICAL REPORT GENERATION MODULE

The Medical Report Generation Module takes the class label generated by the Image Classification Module and uses it to create a detailed medical report. This module translates the class label (e.g., “Polyp”) into an informative report that explains the medical significance of the identified object or condition. The module utilizes natural language processing techniques to form coherent and medically relevant text, ensuring that the output is understandable and useful for medical professionals. This report enhances the diagnostic process by providing clear, context-specific information derived from the image classification results.

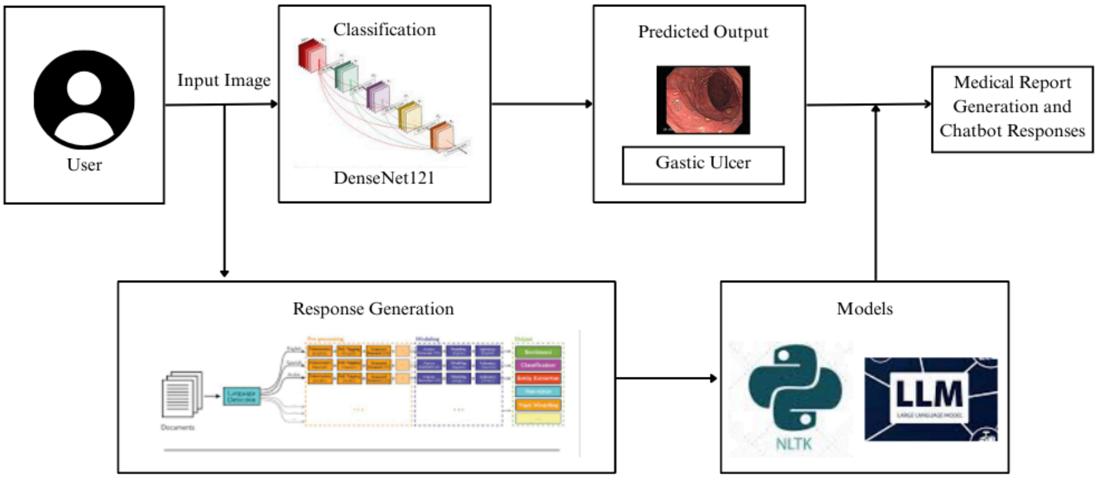


Fig 5.4.4 *Medical Report Generation Module Architecture Diagram*

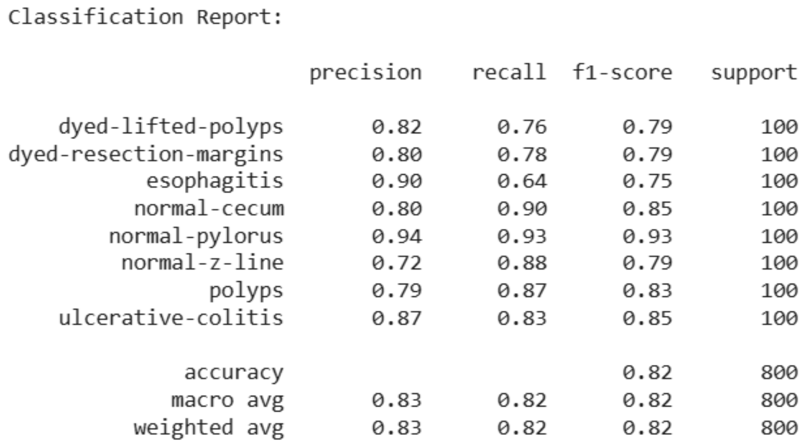
5.4.5 OUTPUT DISPLAY MODULE

The Output Display Module is the final step of the system, responsible for presenting the results to the user in an accessible and user-friendly format. It displays both the predicted class label (e.g., “Polyp”) and the generated medical report. The module ensures that the output is clear and easily interpretable, making it easy for medical practitioners or users to understand the diagnosis. This module is essential for providing an effective user experience, as it ensures that all relevant information is visually presented in a coherent, readable manner, facilitating the decision-making process.

CHAPTER 6

RESULT AND DISCUSSION

The proposed system successfully combines deep learning-based image classification with automated medical report generation for gastrointestinal disease diagnosis. The DenseNet121 model, fine-tuned for this task, achieved an overall accuracy of **82%**, with strong performance in classes like **normal-pylorus (F1-score: 0.93)** and **ulcerative-colitis (F1-score: 0.85)**. Preprocessing techniques such as image resizing and normalization contributed to consistent input quality, enhancing model effectiveness. The medical report generation module accurately translated classification results into relevant, readable summaries. Despite slightly lower recall in cases like **esophagitis (0.64)**, the system maintained balanced macro and weighted F1-scores of **0.82**, indicating reliable overall performance.



```
Classification Report:

                        precision    recall  f1-score   support

     dyed-lifted-polyps       0.82      0.76      0.79       100
dyed-resection-margins       0.80      0.78      0.79       100
            esophagitis       0.90      0.64      0.75       100
           normal-cecum       0.80      0.90      0.85       100
         normal-pylorus       0.94      0.93      0.93       100
          normal-z-line       0.72      0.88      0.79       100
                 polyps       0.79      0.87      0.83       100
     ulcerative-colitis       0.87      0.83      0.85       100

               accuracy                           0.82       800
              macro avg       0.83      0.82      0.82       800
           weighted avg       0.83      0.82      0.82       800
```

Fig 6.1 *Classification Performance Report for Medical Image Categories*

In figure 6.1, the classification report demonstrates strong overall performance of the image classification model, achieving an accuracy of 82% across 8 distinct medical categories, each with 100 samples. The model shows particularly high precision and recall for classes like normal-pylorus (F1-score: 0.93) and normal-cecum (F1-score:

0.85), while performance dips slightly for esophagitis, which has a lower recall (0.64) despite high precision (0.90). The macro and weighted averages for precision, recall, and F1-score are all around 0.82–0.83, indicating that the model maintains consistent performance across both common and less frequent classes. This suggests the classifier is well-suited for balanced medical image datasets with diverse conditions.

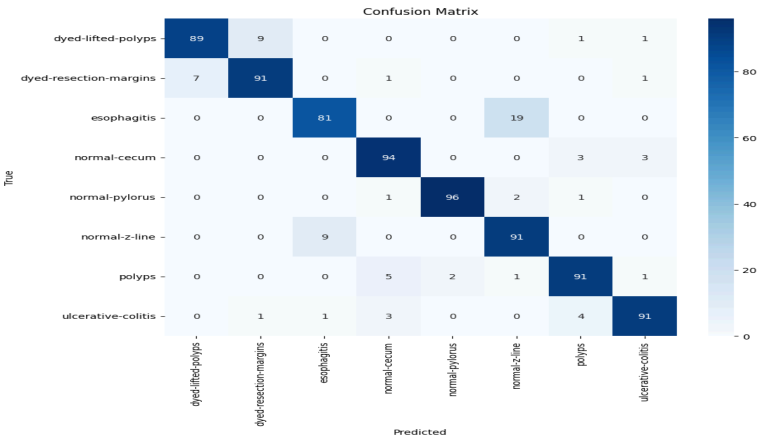
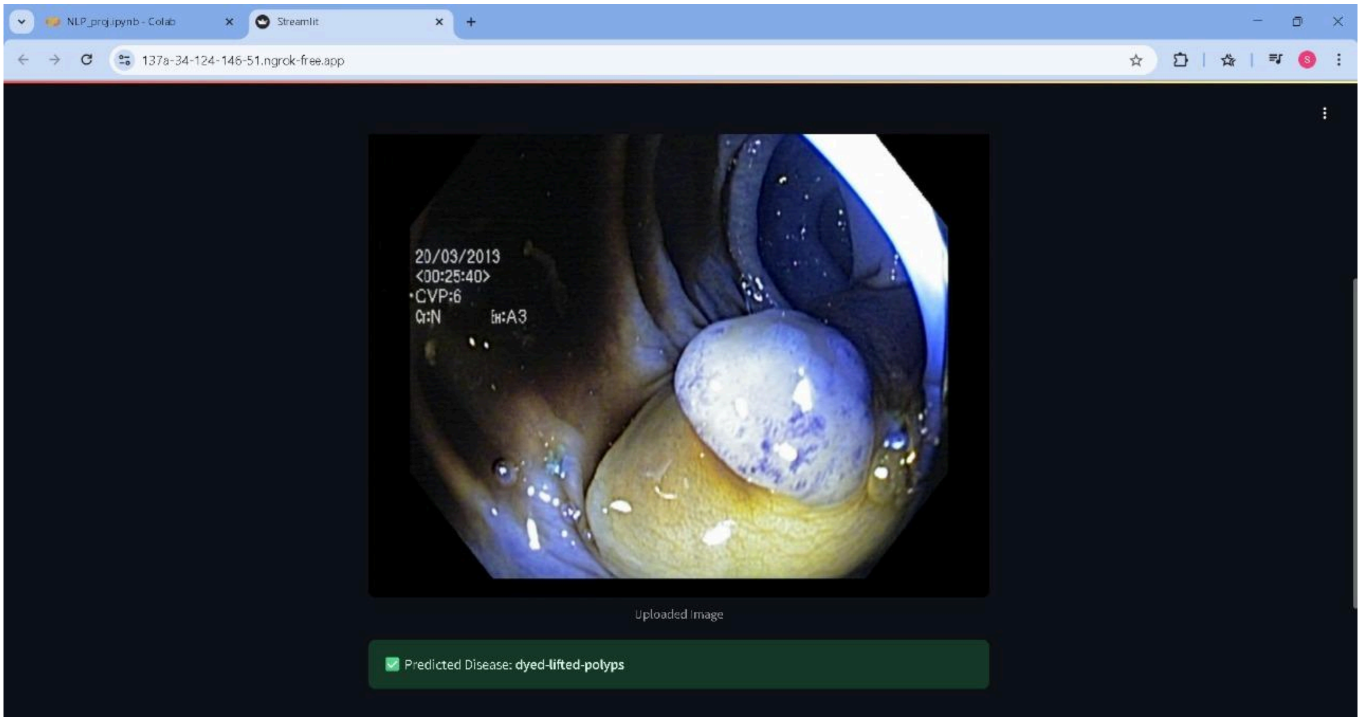


Fig 6.2 *Confusion Matrix for Multi-Class Gastrointestinal Disease Medical Image Classification*

In Figure 6.2, the confusion matrix illustrates the strong classification performance of a deep learning model trained on gastrointestinal medical images across eight categories. High values along the diagonal, such as 96 correct predictions for “normal-pylorus” and 94 for “normal-cecum,” reflect the model’s high accuracy in distinguishing specific conditions. While a few misclassifications occur—like 19 “esophagitis” cases labeled as “normal-z-line”—these are largely between visually or anatomically similar classes. Overall, the matrix highlights the model’s robustness and reliability, supporting its suitability for real-time clinical use in tasks like computer-aided diagnosis and automated gastrointestinal screening.



Uploaded Image

☑ Predicted Disease: **dyed-lifted-polyps**

Fig 6.3 *Predicted gastrointestinal disease*

MATHEMATICAL CALCULATIONS:

1. Accuracy:

Accuracy measures the overall correctness of the model, representing the proportion of true predictions (both true positives and true negatives) among the total number of predictions. It gives a general idea of how well the model performs across all classes. The formula for accuracy is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

In a multi-class setting, this simplifies to:

$$\text{Accuracy} = \frac{\sum TP_i}{\text{Total samples}}$$

From the confusion matrix:

$$\text{Accuracy} = \frac{89 + 91 + 81 + 94 + 96 + 91 + 91 + 91}{800} = \frac{724}{800} = 0.905 = 90.5\%$$

2. SSIM (Structural Similarity Index):

Precision quantifies the ability of the model to correctly predict positive instances of a specific class. High precision indicates a low false positive rate. The formula for precision is:

$$\text{Precision} = \frac{TP}{TP + FP}$$

For example, for class "dyed-lifted-polyps":

$$\text{Precision} = \frac{89}{89 + 7} = \frac{89}{96} \approx 0.927$$

3. Recall (Sensitivity):

Recall measures how well the model identifies all actual positive instances of a class. High recall means few false negatives. The formula for recall is:

$$\text{Recall} = \frac{TP}{TP + FN}$$

For example, for class "dyed-lifted-polyps":

$$\text{Recall} = \frac{89}{89+11} = \frac{89}{100} = 0.89$$

4. F1 Score:

F1 Score is the harmonic mean of Precision and Recall. It balances the trade-off between the two, especially useful when the dataset is imbalanced. The formula for F1 score is:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

For example, for class "dyed-lifted-polyps":

$$F1 = 2 \times \frac{0.927 \times 0.89}{0.927 + 0.89} \approx 0.908$$

APPENDIX

SAMPLE CODE

```
from google.colab import drive
drive.mount('/content/drive')

!pip install tensorflow opencv-python matplotlib

import os
import numpy as np
import cv2
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
import tensorflow as tf
from tensorflow.keras.applications import DenseNet121
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# 1. Load and preprocess dataset
def load_images_and_labels(dataset_path):
    images, labels = [], []
    class_names = sorted(os.listdir(dataset_path))

    for idx, class_name in enumerate(class_names):
        class_path = os.path.join(dataset_path, class_name)
        if os.path.isdir(class_path):
            for filename in os.listdir(class_path):
                img_path = os.path.join(class_path, filename)
                img = cv2.imread(img_path)
                if img is not None:
                    img = cv2.resize(img, (224, 224))
                    images.append(img)
                    labels.append(idx)
    return np.array(images), np.array(labels), class_names
```

```
dataset_path = '/content/drive/MyDrive/kvasir-dataset'
images, labels, class_names = load_images_and_labels(dataset_path)
images = images.astype('float32') / 255.0

# 2. Split data
X_train, X_test, y_train, y_test = train_test_split(images, labels, test_size=0.2,
stratify=labels, random_state=42)

# 3. Convert labels to categorical
num_classes = len(class_names)
y_train_cat = tf.keras.utils.to_categorical(y_train, num_classes)
y_test_cat = tf.keras.utils.to_categorical(y_test, num_classes)

# 4. Image augmentation
datagen = ImageDataGenerator(rotation_range=15, width_shift_range=0.1,
height_shift_range=0.1,
                             zoom_range=0.1, horizontal_flip=True)
datagen.fit(X_train)

# 5. Load DenseNet121 and build model
base_model = DenseNet121(weights='imagenet', include_top=False,
input_shape=(224, 224, 3))
base_model.trainable = False  # Freeze for transfer learning

x = GlobalAveragePooling2D()(base_model.output)
x = Dropout(0.5)(x)
output = Dense(num_classes, activation='softmax')(x)
model = Model(inputs=base_model.input, outputs=output)


# 6. Compile model
model.compile(optimizer=Adam(1e-4), loss='categorical_crossentropy',
metrics=['accuracy'])

# 7. Train model with early stopping
early_stop = EarlyStopping(patience=5, restore_best_weights=True)
history = model.fit(datagen.flow(X_train, y_train_cat, batch_size=32),
                validation_data=(X_test, y_test_cat),
                epochs=25, callbacks=[early_stop])

# 8. Evaluation
y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis=1)
print("\nClassification Report:\n")
print(classification_report(y_test, y_pred_classes, target_names=class_names))

# 9. Fine-tune the model (unfreeze last N layers)
fine_tune_at = 300  # Unfreeze from this layer index onward (can tune based on
performance)

for layer in base_model.layers[:fine_tune_at]:
    layer.trainable = False
for layer in base_model.layers[fine_tune_at:]:
    layer.trainable = True

# Recompile with a lower learning rate
model.compile(optimizer=Adam(1e-5), loss='categorical_crossentropy',
metrics=['accuracy'])

# Train again (fine-tuning)
fine_tune_history = model.fit(datagen.flow(X_train, y_train_cat, batch_size=32),
                              validation_data=(X_test, y_test_cat),
                              epochs=10,
                              callbacks=[early_stop])

import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

y_pred_finetuned = model.predict(X_test)
y_pred_labels = np.argmax(y_pred_finetuned, axis=1)

cm = confusion_matrix(y_test, y_pred_labels)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt="d", xticklabels=class_names,
yticklabels=class_names, cmap="Blues")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("Confusion Matrix")
plt.show()

model.save('kvasir_model.h5')

!pip install streamlit opencv-python tensorflow

!pip install streamlit pyngrok

%%writefile app.py
import streamlit as st
import numpy as np
import cv2
import tensorflow as tf

# Load the trained model
model = tf.keras.models.load_model('/content/kvasir_model.h5')

# Define class names
class_names = [
    'dyed-lifted-polyps',
    'dyed-resection-margins',
    'esophagitis',
    'normal-cecum',
    'normal-pylorus',
    'normal-z-line',
    'polyps',
    'ulcerative-colitis'
]

def preprocess_image(image):
    img = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (224, 224))
    img = img.astype('float32') / 255.0
    img = np.expand_dims(img, axis=0)
    return img

st.title("Gastrointestinal Image Classification")
st.write("Upload an image of a gastrointestinal tract for classification.")

uploaded_file = st.file_uploader("Choose an image...", type=["jpg", "jpeg", "png"])

if uploaded_file is not None:
    image = cv2.imdecode(np.frombuffer(uploaded_file.read(), np.uint8),
cv2.IMREAD_COLOR)
    st.image(image, caption='Uploaded Image', use_container_width=True)

    processed_image = preprocess_image(image)
    prediction = model.predict(processed_image)
    predicted_class = class_names[np.argmax(prediction)]
    st.success(f"Predicted Class: **{predicted_class}**")

!pip install openai==0.28

import openai
openai.api_key =
"sk-proj-S3dJ_J6oj0X96lF2YDB1B3-XZjCHsrpRLVfjZgnebgast2jdpaLcto-9Cv9U
JUH_MgFvyZC7VMT3BlbkFJ1627rFnMgqICzdMHDcWjMjU_LpR0dDBdtcZXP
oTsq093vI_LToDvHzuq9v-E3zOmD_L9rYbpEA"

%%writefile app.py
import streamlit as st
import numpy as np
import cv2
import tensorflow as tf
import openai
import os

# Load your API key from Streamlit secrets or environment variable
openai.api_key =
"sk-proj-S3dJ_J6oj0X96lF2YDB1B3-XZjCHsrpRLVfjZgnebgast2jdpaLcto-9Cv9U
JUH_MgFvyZC7VMT3BlbkFJ1627rFnMgqICzdMHDcWjMjU_LpR0dDBdtcZXP
oTsq093vI_LToDvHzuq9v-E3zOmD_L9rYbpEA"
```

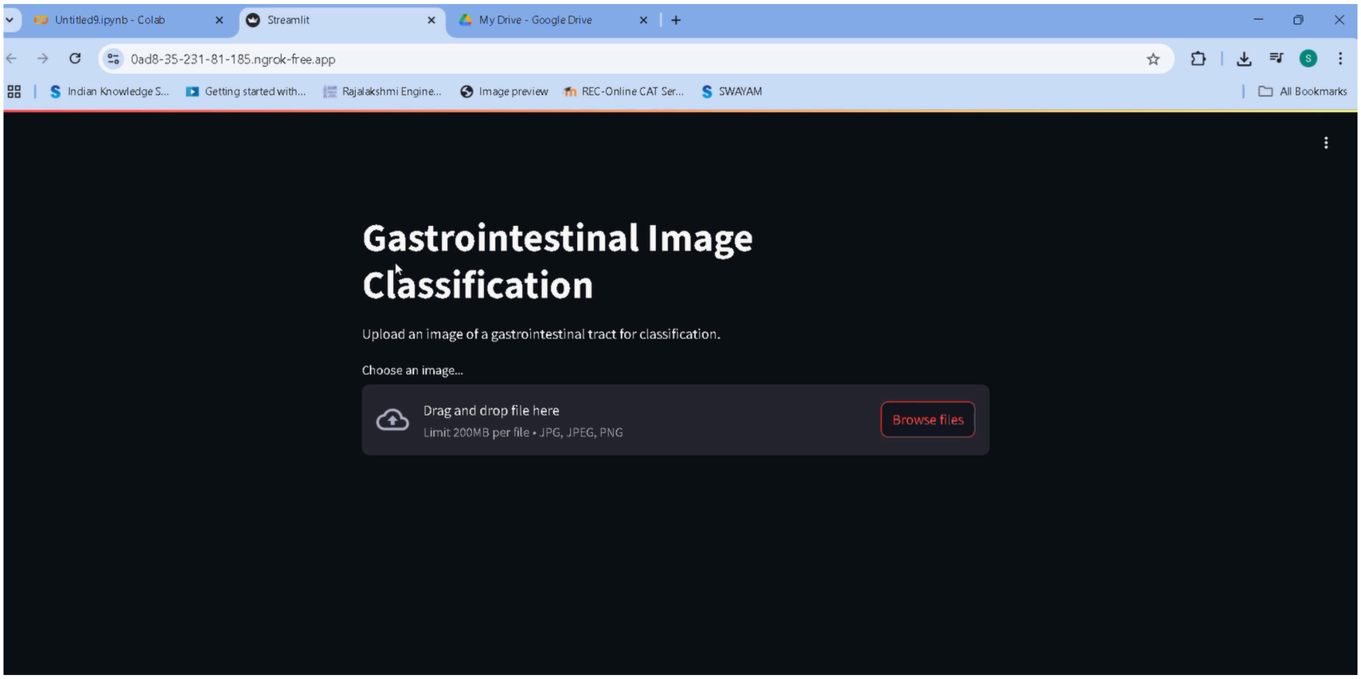
```
# Load the trained model
model = tf.keras.models.load_model('/content/kvasir_model.h5')

# Define class names
class_names = [
    'dyed-lifted-polyps',
    'dyed-resection-margins',
    'esophagitis',
    'normal-cecum',
    'normal-pylorus',
    'normal-z-line',
    'polyps',
    'ulcerative-colitis'
]

def preprocess_image(image):
    img = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (224, 224))
    img = img.astype('float32') / 255.0
    img = np.expand_dims(img, axis=0)
    return img

def ask_gpt(question, disease):
    prompt = f"You are a medical assistant. The disease detected is '{disease}'. Answer the user's question about this condition.\n\nUser: {question}\nAssistant:"
    try:
        response = openai.ChatCompletion.create(
            model="gpt-3.5-turbo",  # or "gpt-4" if available
            messages=[{"role": "user", "content": prompt}],
            max_tokens=150
        )
        return response.choices[0].message.content.strip()
    except Exception as e:
        return f"❌ Error: {e}"

st.title("🩺 Gastrointestinal Image Classification + GPT Chatbot")
st.write("Upload an image of a gastrointestinal tract for classification.")
```

```
uploaded_file = st.file_uploader("Choose an image...", type=["jpg", "jpeg", "png"])

if uploaded_file is not None:
        image = cv2.imdecode(np.frombuffer(uploaded_file.read(), np.uint8),
cv2.IMREAD_COLOR)
    st.image(image, caption='Uploaded Image', use_container_width=True)

    processed_image = preprocess_image(image)
    prediction = model.predict(processed_image)
    predicted_class = class_names[np.argmax(prediction)]

    st.success(f"✅ Predicted Class: **{predicted_class}**")

    # GPT chatbot section
    st.subheader("💬 Ask GPT about this condition")
    user_question = st.text_input("Ask a question about the detected condition:")

    if user_question:
        with st.spinner("Consulting medical assistant..."):
            response = ask_gpt(user_question, predicted_class)
        st.write(response)

!pip install transformers huggingface_hub

from huggingface_hub import login

# Authenticate with your Hugging Face account
login(token="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")

%%writefile app.py
import streamlit as st
import numpy as np
import cv2
import tensorflow as tf
from transformers import AutoTokenizer, AutoModelForQuestionAnswering,
pipeline
```

```
# Load Keras model
model = tf.keras.models.load_model('/content/kvasir_model.h5')

# Disease class names
class_names = [
    'dyed-lifted-polyps',
    'dyed-resection-margins',
    'esophagitis',
    'normal-cecum',
    'normal-pylorus',
    'normal-z-line',
    'polyps',
    'ulcerative-colitis'
]

# Preprocess input image
def preprocess_image(image):
    img = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (224, 224))
    img = img.astype('float32') / 255.0
    img = np.expand_dims(img, axis=0)
    return img

# Streamlit interface
st.title("🩺 Gastrointestinal Disease Classifier + BioBERT Q&A")
st.write("Upload a GI tract image to classify and ask questions based on results.")

# Upload image
uploaded_file = st.file_uploader("Upload an image...", type=["jpg", "jpeg", "png"])

if uploaded_file:
    # Read and display uploaded image
    image = cv2.imdecode(np.frombuffer(uploaded_file.read(), np.uint8),
cv2.IMREAD_COLOR)
    st.image(image, caption='Uploaded Image', use_container_width=True)

    # Preprocess and predict disease
    processed = preprocess_image(image)
    prediction = model.predict(processed)
    predicted_class = class_names[np.argmax(prediction)]
    st.success(f"✅ Predicted Disease: **{predicted_class}**")

    # Load BioBERT model for Q&A
                                                              tokenizer =
AutoTokenizer.from_pretrained("ktrapeznikov/biobert_v1.1_pubmed_squad_v2")
                                                              model =
AutoModelForQuestionAnswering.from_pretrained("ktrapeznikov/biobert_v1.1_pu
bmed_squad_v2")
    qa_pipeline = pipeline("question-answering", model=model, tokenizer=tokenizer)

    # Q&A section
    st.header("Ask a medical question about the result")
    question = st.text_input("Type your question below:")

    if question:
        context = f"The predicted condition is {predicted_class}.Gastrointestinal (GI)
diseases refer to disorders involving the digestive tract, including the esophagus,
stomach, small intestine, large intestine, rectum, liver, gallbladder, and pancreas.
Common symptoms include abdominal pain, bloating, diarrhea, constipation,
nausea, and vomiting. Some prevalent GI disorders are irritable bowel syndrome
(IBS), gastroesophageal reflux disease (GERD), and Crohn's disease."
        answer = qa_pipeline(question=question, context=context)
        st.info(f"💬 Answer: **{answer['answer']}**")

!ngrok config add-authtoken
2wPAqYdyaz3VAiydydWDg54gjm2_XRkEXg5zNK9kUD4DKeQn
from pyngrok import ngrok

# Kill all ngrok processes to ensure a clean start
!killall ngrok

# Start the Streamlit app in the background
!streamlit run app.py &>/content/log.txt &

# Connect to the Streamlit app using ngrok and get the public URL
url = ngrok.connect(8501)
```

```
print("Streamlit app running at:", url)  # Now 'url' is defined and can be used

# If you need to disconnect later, you can use:
# ngrok.disconnect(url.public_url)
```

OUTPUT SCREENSHOTS



Gastrointestinal Image Classification

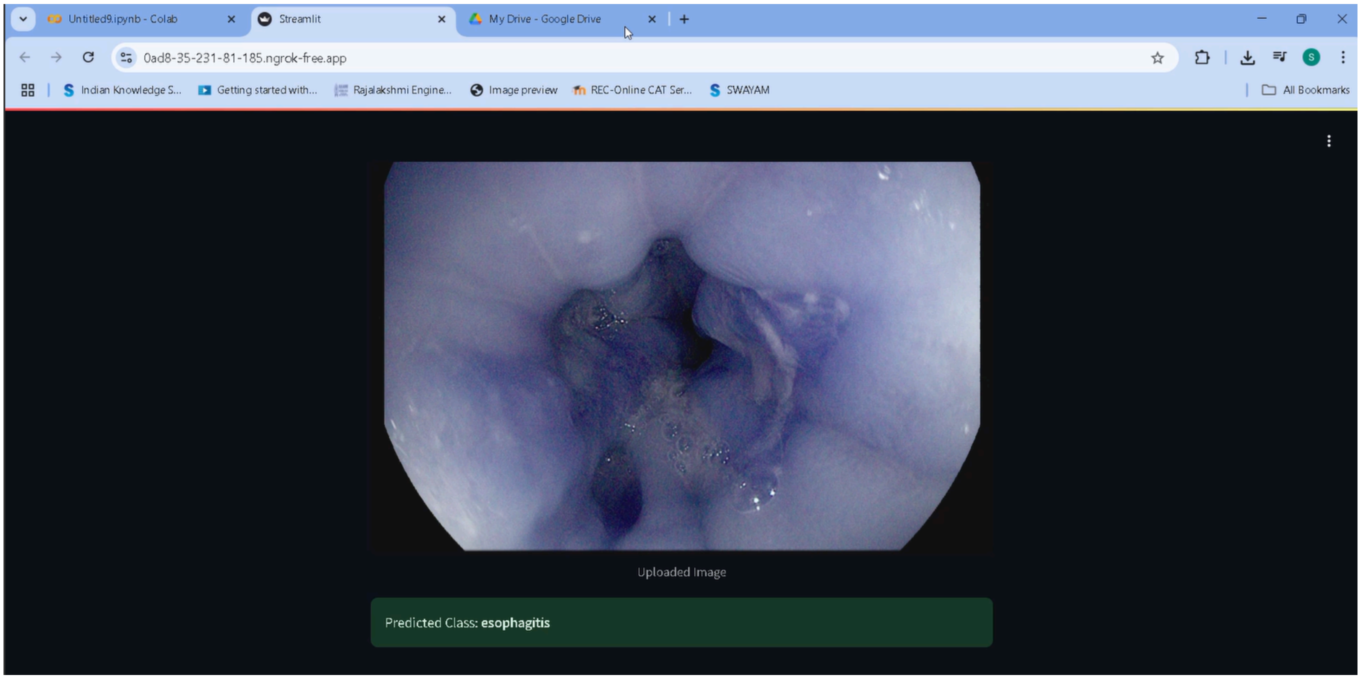
Upload an image of a gastrointestinal tract for classification.

Choose an image...

Drag and drop file here

Limit 200MB per file • JPG, JPEG, PNG

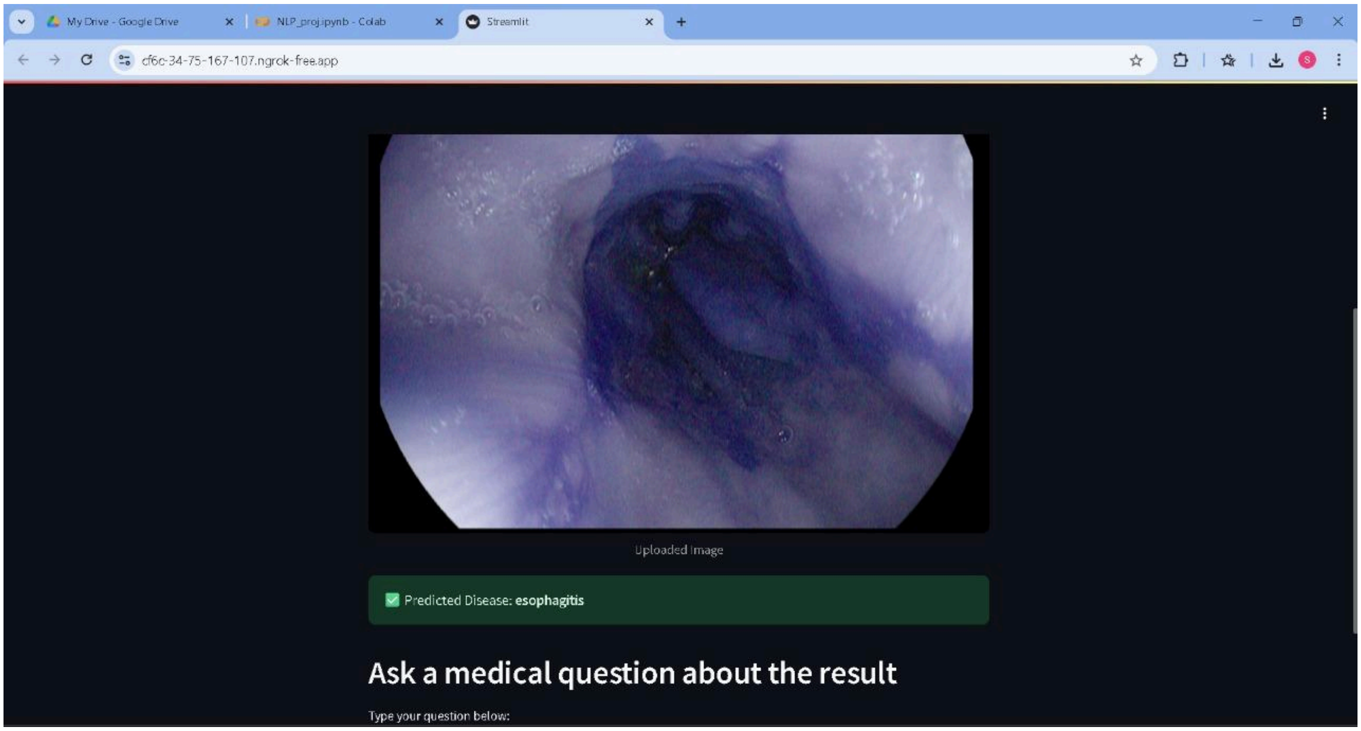
Fig A.1 *User interface of importing file*



Uploaded Image

Predicted Class: **esophagitis**

Fig A.2 *Predicted gastrointestinal disease*



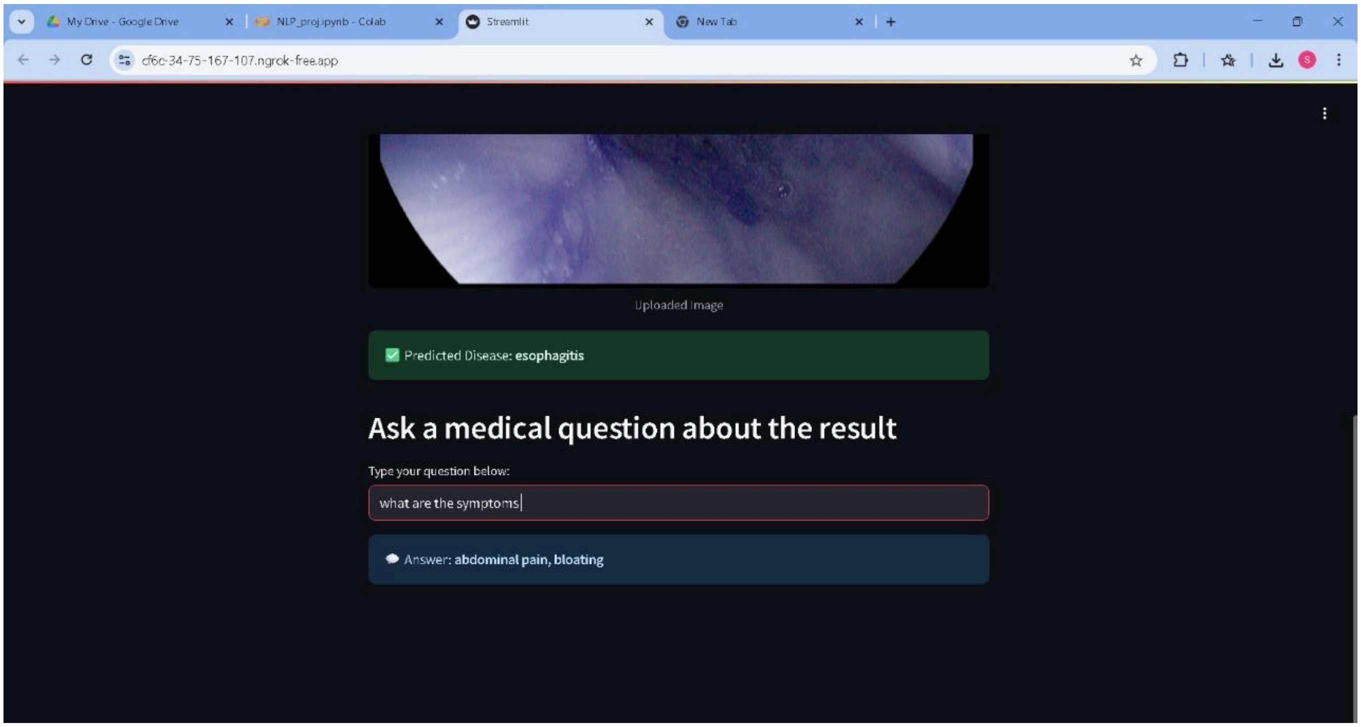
Uploaded Image

☑ Predicted Disease: **esophagitis**

Ask a medical question about the result

Type your question below:

Fig A.3 *Chatbot interface*



Uploaded Image

☑ Predicted Disease: **esophagitis**

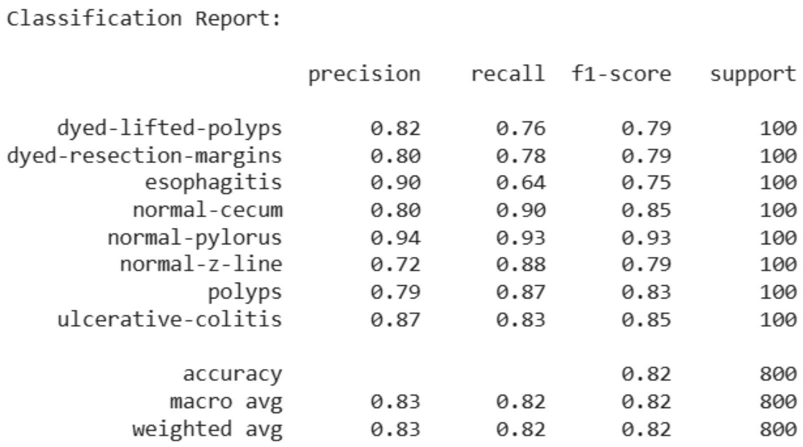
Ask a medical question about the result

Type your question below:

what are the symptoms

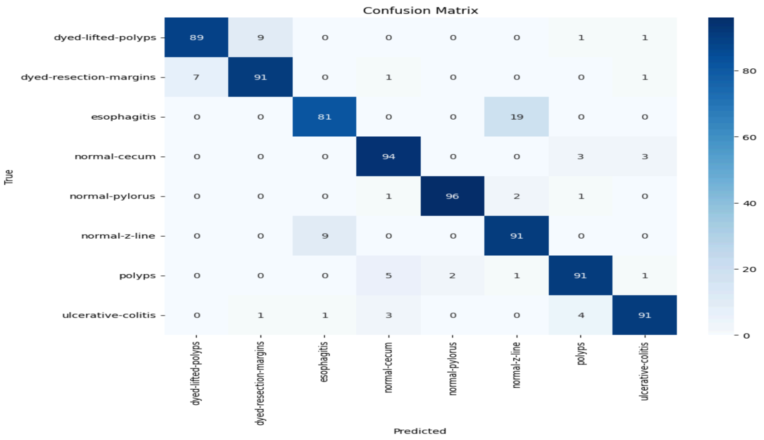
Answer: **abdominal pain, bloating**

Fig A.4 *Generating answer in the chatbot*



```
Classification Report:

                         precision    recall  f1-score   support

     dyed-lifted-polyps       0.82      0.76      0.79       100
dyed-resection-margins       0.80      0.78      0.79       100
           esophagitis       0.90      0.64      0.75       100
          normal-cecum       0.80      0.90      0.85       100
        normal-pylorus       0.94      0.93      0.93       100
         normal-z-line       0.72      0.88      0.79       100
                polyps       0.79      0.87      0.83       100
    ulcerative-colitis       0.87      0.83      0.85       100

              accuracy                           0.82       800
             macro avg       0.83      0.82      0.82       800
          weighted avg       0.83      0.82      0.82       800
```

Fig A.5 *Classification Performance Report for Medical Image Categories*



Confusion Matrix

	dyed-lifted-polyps	dyed-resection-margins	esophagitis	normal-cecum	normal-pylorus	normal-z-line	polyps	ulcerative-colitis
dyed-lifted-polyps	89	9	0	0	0	0	1	1
dyed-resection-margins	7	91	0	1	0	0	0	1
esophagitis	0	0	81	0	0	19	0	0
normal-cecum	0	0	0	94	0	0	3	3
normal-pylorus	0	0	0	1	96	2	1	0
normal-z-line	0	0	9	0	0	91	0	0
polyps	0	0	0	5	2	1	91	1
ulcerative-colitis	0	1	1	3	0	0	4	91

Fig A.6 *Confusion Matrix for Multi-Class Gastrointestinal Disease Medical Image Classification*

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