ENHANCED IMAGE PROCESSING TECHNIQUES FOR ACCURATE FEATURE EXTRACTION IN GASTROINTESTINAL DISEASE DETECTION

PROJECT WORK - PHASE-1 REPORT

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In partial fulfillment for the award of the degree

Of

BACHELOR OF ENGINEERING

In

ELECTRONICS AND COMMUNICATION ENGINEERING

Under the guidance of

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INSTITUTE OF SCIENCE, TECHNOLOGY & ADVANCED STUDIES (VISTAS)
(Deemed to be University Estd. u/s 3 of the UGC Act, 1956)
PALLAVARAM, THALAMBUR, PERIYAPALAYAM-CHENNAI
ACCREDITED BY NAAC WITH 'A++' GRADE

VISTAS, CHENNAI-600117

November 2024

BONAFIDE CERTIFICATE

Certified that this project report titled "**ENHANCED IMAGE PROCESSING TECHNIQUES FOR ACCURATE FEATURE EXTRACTION IN GASTROINTESTINAL DISEASE DETECTION**" is the bonafide work of **N.SHANMUKHA SAI (Reg No: 21603107) and E.AARTHI (Reg No: 21603116)** who carried out the project work under my supervision. Certified further that to the best of my knowledge, the work reported here in does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ACKNOWLEDGEMENT

We wish to express our heartfelt gratitude and thanks to our founder chairman Shri. Ishari K. Ganesh for providing a good infrastructural support with all kinds of lab facilities to do the project work successfully.

We wish to express my heartfelt thanks to **Dr. ISHARI K GANESH**,Chancellor **Dr. A. JOTHI MURUGAN**, **Dr. ARTHI K.GANESH** pro-chancellor (P&D), **Dr**. **PREETHAA GANESH**, Vice President, VELS Group of Institutions,**Dr. S. SRIMAN NARAYANAN**, Vice Chancellor,**Dr.M.BHASKARAN** Pro Vice Chancellor, **Dr. P. SARAVANAN**, Registrar and **Dr. A. UDHAYAKUMAR** Controller of Examinations for providing us necessary facilities to accomplish this project work and permitting us to undertake the research program.

We wish to express our sincere thanks to **Dr. C.ARUN,** Dean, School of Engineering, Vels Institute of Science Technology & Advanced Studies (VISTAS) for his good counsel, encouragement, valuable suggestions and support rendered at all times of our project work.

We wish to express our sincere thanks to **Dr. S. JERRITTA**, Head of the Department, Department of Electronics and Communication Engineering, VELS Institute of Science Technology & Advanced Studies (VISTAS), for her valuable guidance and the facilities provided to us.

We are indebted to our project Coordinators **Dr.V.RAJENDRAN**, Professor/Director and **Dr. MADONA B SAHAAI**, Assistant Professor Department of ECE for their motivation, guidance and valuable suggestions given to us throughout our discussions and reviews. This gave us the driving force for us to proceed with our project work with new innovative methods. We are grateful to them to move forward in our career and life.

We also wish to express our sincere thanks to our Supervisor **Dr. MADONA B SAHAAI**, Assistant Professor, Department of Electronics and Communication Engineering, VISTAS for providing valuable suggestions to us to carry out this project by constant monitoring and continuous encouragement at various stages of the work and the motivation, guidance and valuable suggestions given to us throughout our discussions and reviews. This gave us the driving force for us to proceed with our project work with new innovative techniques.

We would also like to thank all teaching and non-teaching staff of our department for their unfailing support for our project work to this extent.

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ABSTRACT

Gastrointestinal (GI) diseases like ulcers, polyps, and GI bleeding require precise diagnosis to ensure effective treatment. This project enhances diagnostic accuracy by combining image processing techniques with a Convolutional Neural Network (CNN) model to classify endoscopic images into four categories: Polyp Cells Detection, Bleeding Identification, Normal Stage, and Ulcer Abnormal Stage. By removing noise and emphasizing key features, our image processing techniques improve the clarity and quality of images, enabling the CNN to focus on critical patterns unique to each condition. The CNN then classifies these enhanced images with greater accuracy, assisting in the early detection of GI abnormalities. This approach aims to support healthcare providers by offering a reliable, automated diagnostic tool that can improve the precision of GI disease detection and aid in timely, non-invasive diagnostics.

KEYWORDS: Gastrointestinal diseases, polyps, GI bleeding, image accuracy,Ulcer, CNN algorithm,health care, automated diagnostic tool.

CHAPTER-1
INTRODUCTION

1.1 Background and Context :

1.1.1.The Importance of Diagnostic Accuracy in Identifying Gastric Cancer Diseases:

Accurate identification of gastric cancer and other gastrointestinal (GI) diseases is crucial due to the significant impact these conditions have on patient health and survival rates. Gastric cancer is often asymptomatic in its early stages, which leads to delayed diagnoses and limited treatment options. For many patients, the disease is only detected at an advanced stage, where the likelihood of effective treatment and recovery is considerably reduced. Therefore, achieving diagnostic accuracy is essential, as early detection dramatically improves prognosis, allowing for timely interventions and potentially life-saving treatments. Advanced image processing and classification technologies, such as those using Convolutional Neural Networks (CNNs), play an increasingly important role in distinguishing between benign and malignant tissues, thus enabling clinicians to make more informed and accurate decisions.

Gastrointestinal (GI) diseases, including ulcers, polyps, and GI bleeding, pose significant health risks and demand precise diagnosis to ensure timely and effective treatment. In recent years, image processing has become an indispensable tool across fields such as healthcare, forensics, security, and automation, offering advanced techniques for analyzing complex images. This project aims to harness these capabilities by applying specialized image processing steps to enhance endoscopic images, overcoming challenges such as noise, variable lighting, and anatomical complexities that can obscure essential diagnostic details.

Beginning with noise reduction and edge sharpening, the approach progresses through segmentation and feature extraction to refine and highlight critical patterns in each image. Using a Convolutional Neural Network (CNN), the processed images are then classified into four categories—Polyp Cells Detection, Bleeding Identification, Normal Stage, and Ulcer Abnormal Stage—enabling accurate and reliable diagnosis. By providing a more precise automated diagnostic tool, this approach supports healthcare providers in early, accurate identification of GI conditions, ultimately contributing to better patient outcomes and improved standards of care.

1.1.2.Challenges in Achieving Diagnostic Accuracy in Gastric Cancer Detection:

Obtaining diagnostic accuracy in the detection of gastric cancer presents several challenges, primarily stemming from the complexity of interpreting endoscopic images. The presence of noise, varying illumination, and intricate anatomical structures can obscure critical features, making it difficult for healthcare professionals to distinguish between malignant and benign conditions. Furthermore, the manual interpretation of images is inherently subjective, leading to potential inconsistencies and errors among different clinicians. These challenges can result in misdiagnoses or delayed detection, adversely affecting patient outcomes. To address these issues, this project employs advanced image processing techniques combined with a Convolutional Neural Network (CNN) model. By utilizing noise reduction and edge sharpening techniques, followed by effective segmentation and feature extraction, our method enhances the clarity of endoscopic images and highlights essential patterns indicative of gastric cancer. The CNN model then accurately classifies these images into relevant categories, minimizing human error and improving diagnostic consistency. This integrated approach not only streamlines the diagnostic process but also supports healthcare providers in making informed decisions, ultimately leading to better patient care and outcomes.

1.2 Significance of accurate and automated GI disease Detector:

Accurate and automated gastrointestinal disease detection is transformative in healthcare, providing early diagnosis and reducing human error, which is critical for improving patient outcomes. These systems use advanced image processing and machine learning techniques to detect subtle abnormalities, ensuring higher diagnostic accuracy and reducing the chances of misdiagnosis. By streamlining workflows, they free up time for medical professionals to focus on complex cases, enhancing efficiency and reducing physician fatigue. Automated detection is particularly valuable in remote or underserved areas, where access to specialists may be limited, as it allows for reliable diagnostics via telemedicine. This approach is also cost-effective, reducing the need for invasive procedures and lowering treatment expenses, especially for late-stage diseases. Additionally, automated systems enable personalized treatment plans by analyzing specific disease characteristics, supporting the broader goal of precision medicine. Finally, data from these systems aids in medical research, helping to refine diagnostic tools and improve disease management over time.

1.2.1 Leveraging Technology, AI, and Advanced Algorithms for Accurate Predictions and Enhanced Image Processing in Gastrointestinal Disease Detection

The integration of technology, artificial intelligence (AI), and sophisticated algorithms plays a pivotal role in enhancing the accuracy and efficiency of gastrointestinal (GI) disease detection. In this project, AI-driven models, such as Convolutional Neural Networks (CNNs), analyze complex medical images to detect patterns and anomalies that are often challenging to identify manually. Image processing techniques, like Gaussian and median filtering, help reduce noise and sharpen details, enabling more precise feature extraction. Segmentation algorithms further isolate regions of interest, allowing the system to focus on potential areas of concern. Through high-saturation adjustments and enhancement methods, image clarity is improved, making features like lesions or irregular tissue more distinguishable. These AI-enhanced processing techniques enable rapid, reliable, and consistent analysis, reducing human error and supporting healthcare professionals in making informed diagnostic decisions. This fusion of AI and advanced algorithms not only improves diagnostic accuracy but also increases accessibility to quality healthcare,

1.2.2 Importance of CNN for Classification in GI Disease Detection:

Convolutional Neural Networks (CNNs) are ideal for classification in gastrointestinal disease detection due to their ability to automatically learn and extract complex features from medical images. CNNs use multiple layers to capture spatial and hierarchical patterns, such as edges, shapes, and textures, which are crucial for identifying anomalies in the GI tract. By handling large image datasets, CNNs improve accuracy and reduce the need for manual feature engineering, making them highly effective for medical image classification. Their deep learning capabilities allow for precise differentiation between healthy and diseased tissues, enhancing diagnostic reliability and supporting early detection of conditions like cancer and inflammation.

1.2.3. How it Supports for medical Research and Innovation:

The data generated from automated GI disease detection contributes to ongoing medical research, offering valuable insights into disease patterns, patient demographics, and treatment efficacy. This data aids researchers in discovering new biomarkers, refining diagnostic algorithms, and developing innovative treatments, advancing the field of gastroenterology.

1.2.4. Disease Description :

Polyps are abnormal tissue growths that form on the inner lining of organs, commonly found in the gastrointestinal (GI) tract, especially in the colon. While most polyps are benign, some have the potential to become cancerous over time, particularly adenomatous polyps, which are considered precancerous. The development of polyps is often associated with factors like genetics, age, obesity, smoking, and a diet high in fat. They usually do not cause symptoms and are often detected during routine screenings like colonoscopies. However, larger polyps may cause symptoms such as rectal bleeding, changes in stool color, or abdominal pain. Early detection and removal of polyps are crucial to prevent their progression to colorectal cancer.

There are several types of polyps, including hyperplastic, adenomatous, and serrated polyps, each with varying cancerous potential. Treatment generally involves the removal of polyps through endoscopic procedures to prevent malignancy. In some cases, especially with larger or numerous polyps, more frequent surveillance is recommended. Lifestyle changes, such as a diet high in fiber, regular exercise, and reduced alcohol and tobacco use, may help lower the risk of polyp formation. Understanding the nature of polyps and their potential to turn cancerous is essential for early intervention and prevention of gastrointestinal cancers.

Gastrointestinal (GI) bleeding refers to any form of bleeding that occurs in the digestive tract, which can range from mild to life-threatening. It is classified based on its location as either upper GI bleeding (originating from the esophagus, stomach, or duodenum) or lower GI bleeding (from the small intestine, colon, or rectum). Common causes of upper GI bleeding include peptic ulcers, gastritis, esophageal varices, and gastric cancer, while lower GI bleeding can result from conditions like diverticulosis, inflammatory bowel disease, hemorrhoids, or colorectal cancer. Symptoms can vary depending on the source and severity of the bleed, ranging from black, tarry stools (melena) to bright red blood in the stool (hematochezia) or vomiting blood (hematemesis).

Diagnosing GI bleeding involves a combination of physical examinations, lab tests, and imaging techniques such as endoscopy or colonoscopy to identify the source. Treatment depends on the severity and cause of the bleeding; it may include medications to reduce stomach acid, endoscopic procedures to cauterize bleeding vessels, or surgery in severe cases. In emergency scenarios, blood transfusions may be necessary to stabilize patients. Early detection and treatment are crucial in preventing complications like anemia, shock, or death, particularly in severe cases of GI bleeding.

ulcer is an open sore or lesion that develops on the lining of the stomach, small intestine, or esophagus, typically due to damage caused by stomach acid. The most common types are peptic ulcers, which are further classified as gastric ulcers (in the stomach) and duodenal ulcers (in the first part of the small intestine). These ulcers often result from infection with the bacterium *Helicobacter pylori* or the prolonged use of nonsteroidal anti-inflammatory drugs (NSAIDs) like aspirin and ibuprofen. Symptoms include burning stomach pain, bloating, heartburn, and in severe cases, vomiting blood or passing black stools, which indicate bleeding.

The diagnosis of ulcers involves endoscopy to visually examine the stomach lining, as well as tests for *H. pylori* infection. Treatment usually includes a combination of antibiotics to eradicate *H. pylori* (if present) and proton pump inhibitors (PPIs) to reduce stomach acid production, allowing the ulcer to heal. Lifestyle modifications such as reducing stress, avoiding alcohol, quitting smoking, and altering the diet can help prevent ulcers or reduce the risk of recurrence. Without treatment, ulcers can lead to serious complications like perforation, bleeding, or the development of scar tissue that obstructs the digestive tract.

CHAPTER -2

LITERATURE SURVEY

2.1 Authors : Qiwang ; Hao Feng ; Weijian Fan

Title : Error feedback sampling for CNN training in upper gastrointestinal diseases classification

In this study, the authors applied convolutional neural networks (CNNs) to classify upper gastrointestinal diseases from medical images, focusing on improving training speed and accuracy. To address this, they introduced error feedback sampling, a method that reintroduces misclassified samples during training.

Their main achievement is a significant boost in model accuracy and robustness, as error feedback sampling allows the model to better learn from challenging cases. This approach outperformed traditional sampling methods, enhancing the model's ability to generalize in upper GI disease classification.

The authors' contribution highlights the effectiveness of error feedback sampling for medical image analysis, specifically improving CNN training for disease detection. This method enhances diagnostic reliability, offering promise for more accurate and efficient healthcare models.

2.2 Authors : Qian Zhao ; Wenming Yang ; Qingmin Liao

Title : AFA-RN: An Abnormal Feature Attention Relation Network for Multi-class Disease Classification in gastrointestinal endoscopic images.

Gastrointestinal diseases pose a significant public health risk, where early detection can reduce mortality rates. Wireless capsule endoscopy (WCE) is widely used to examine these diseases, producing thousands of images per session. However, only a small portion show disease-related features, making manual review time-consuming for doctors. Automated classification algorithms for WCE images could greatly assist in this process.

Traditional deep learning approaches need large, labeled datasets, but these are difficult to obtain due to the need for expert annotation. This challenge is compounded by the rarity of some disease types, resulting in imbalanced datasets. To address these issues, the authors propose the Abnormal Feature Attention Relationship Network (AFA-RN), which uses feature addition, concatenation, and bilinear merging to focus more effectively on abnormal features.

AFA-RN enhances classification by applying few-shot learning, improving performance on multi-category disease classification, even with limited data. This approach reduces dependency on extensive labeled datasets and offers higher accuracy in dealing with imbalanced classes, showing potential for more effective automated WCE image analysis.

2.3 Authors : Wenju Du ; Nini Rao ; Dingyun Liu ; Hongxiu Jiang ; Chengsi Luo ; Zhengwen Li

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

Gastrointestinal (GI) diseases are a major global health concern, where early detection is key to better patient outcomes. Endoscopic methods like gastroscopy, colonoscopy, and wireless capsule endoscopy (WCE) are vital tools for examining GI diseases. Each WCE procedure produces thousands of images, with only a small portion showing abnormalities, making manual review challenging for medical professionals. Computer-aided diagnosis (CAD) systems using deep learning (DL) aim to automate GI lesion detection, boosting diagnostic accuracy and efficiency.

Convolutional neural networks (CNNs) have excelled in this area, surpassing traditional methods for detecting polyps, bleeding, and early cancers. However, DL models need extensive labeled data, which is hard to obtain in medical fields due to the need for expert annotations. GI datasets often face class imbalances, making it difficult for models to generalize across rare disease types. Techniques like transfer learning, data augmentation, and few-shot learning help address these limitations.

Advanced models, such as the Abnormal Feature Attention Relationship Network (AFA-RN), employ feature concatenation and bilinear merging to better capture abnormal patterns, improving performance in multi-class GI disease classification. These innovations underscore the value of DL-based CAD systems in aiding clinicians, reducing their workload, and enhancing the accuracy of GI disease diagnosis.

2.4 Authors:Aman Srivatsava,Saurav Sengupta,Sung-jun-kang,Karan Kant,Mariam Khan.

Title : Deep Learning for Detecting Diseases in Gastrointestinal Biopsy Images

This project aimed to harness the potential of machine learning and computer vision to advance diagnostic accuracy in pathology, specifically for gastrointestinal biopsy images. By utilizing deep learning, the authors sought to reduce diagnostic delays and achieve higher accuracy than conventional analysis methods. They focused on applying state-of-the-art deep learning models, typically used in natural image recognition, to detect distinguishing features in biopsy slides of tissues affected by enteropathies.

To achieve this output, the authors used advanced deep learning techniques to analyze and classify specific patterns within biopsy images, enabling both clustering and classification of detected anomalies. Their approach allows for learning across different regions of an image, helping the model identify similar patterns when new biopsy images are introduced.

Through their contribution, the project showcases how cutting-edge technology can support automated and efficient detection of GI-related anomalies, aiding pathologists in identifying critical diagnostic features in medical images. This work contributes a novel application of deep learning architectures in the medical imaging of gastrointestinal biopsy slides, advancing diagnostic capabilities in the field of pathology.

2.5 Authors : Jessica Paola Escobar ; Natalia Gomez ; Karen Sanchez ; Henry Arguello

Title : Hierarchical Deep Convolutional Neural Networks for Multi-category Diagnosis of Gastrointestinal Disorders on Histopathological Images

The automated classification of gastrointestinal (GI) pathologies in endoscopic images is increasingly crucial in gastroenterology, aimed at improving diagnostic speed and accuracy. CNNs are commonly used in GI disease classification due to their robust image-processing capabilities. Techniques such as transfer learning are often adopted, especially given the limited availability of large, annotated medical datasets, allowing models to leverage pre-existing knowledge from non-medical datasets like ImageNet.

Previous studies have focused on identifying specific GI abnormalities, such as lesions and polyps, often using CNN architectures like ResNet, DenseNet, and VGG. These models are sometimes combined in ensembles to enhance feature extraction capabilities. However, training CNNs from scratch can be challenging due to small datasets, resulting in less optimal classification performance.

This study utilizes CNN-based transfer learning on the Kvasir dataset, comprising 8,000 labeled endoscopic images across eight categories that include both anatomical structures and GI pathologies. By fine-tuning pre-trained CNN models, the study achieves an accuracy of 94.6%, improving upon previous methods by as much as 13.6%. The combined use of transfer learning, data augmentation, and fine-tuning underscores the method's promise in advancing diagnostic accuracy and efficiency in GI disease detection.

2.6.Authors:AmitKumarKundu ; ShaikhAnowarulFattah ; Khan A. Wahid.

Title : Least Square Saliency Transformation of Capsule Endoscopy Images for PDF Model Based Multiple Gastrointestinal Disease Classification

They aimed to improve diagnostic accuracy in identifying gastrointestinal (GI) diseases from histopathological biopsy images. GI disorders present challenges for classification due to similar features across different sections of the GI tract and shared characteristics among various diseases, making it difficult to achieve precise diagnostics using standard image classification models.

To address these challenges, the researchers propose a hierarchical classification approach by embedding class hierarchies within a modified VGGNet model. This hierarchical CNN structure allows the model to separately assess each sub-class within the broader class categories, optimizing the model's focus on specific diagnostic features. The model was trained and tested on a large set of image patches derived from whole-slide images (WSIs) collected from multiple patients.

Their contribution for The hierarchical model outperformed traditional flat models in classification accuracy, showing its effectiveness in handling multi-category GI diagnoses. By using a single, integrated model across classification levels, it reduces computational cost while improving diagnostic precision. This model's innovative architecture demonstrates a promising direction for GI pathology, providing a more reliable and efficient tool for clinical diagnostics.

2.7 Karen Sanchez,Henry Arguello,NAtalia Gomez,Jessica Paola Escobar.

Title:Transfer Learning with Convolutional Neural Network for Gastrointestinal Diseases Detection using Endoscopic Images

Accurate classification of pathologies in endoscopic images is critical in Gastroenterology, where automated solutions can significantly aid diagnosis. A recent approach using convolutional neural networks (CNNs) and transfer learning achieved 94.6% accuracy on 8000 images from the Kvasir dataset, representing eight classes of gastrointestinal landmarks and anomalies. This method improved classification precision by 2.1% over previous techniques, demonstrating the potential of machine learning in enhancing medical diagnostics.

The study employed fine-tuning on the VGG16 CNN, pre-trained on ImageNet, along with data augmentation and optimized hyperparameters to achieve high accuracy. This underscores the effectiveness of transfer learning in supporting medical decisions, showing that CNNs are a promising tool for accurate, automated diagnosis in Gastroenterology.

2.8 Authors : **Ikenoyama Y, Hirasawa T, Ishioka M, Namikawa K, Yoshimizu S, Horiuchi Y, Ishiyama A, Yoshio T, Tsuchida T, Takeuchi Y, Shichijo S, Katayama N, Fujisaki J, Tada T.**

Title : Detecting early gastric cancer: Comparison between the diagnostic ability of convolutional neural networks and endoscopists.

This project leverages deep learning, specifically convolutional neural networks (CNNs), to improve early gastric cancer detection, which can be challenging even for experienced endoscopists. The CNN was trained on 13,584 endoscopic images from 2,639 cancer lesions and tested against 67 endoscopists using a set of 800 images. The goal was to determine if the CNN could outperform human experts.

Results showed the CNN had a sensitivity of 58.4%, significantly higher than the 31.9% achieved by endoscopists. Additionally, the CNN processed the images in just 45.5 seconds, compared to the 173 minutes taken by endoscopists. While the CNN demonstrated quicker analysis and higher sensitivity, it still had issues with specificity. Further improvements are needed, but this AI system shows promise as a diagnostic aid to support endoscopists in detecting early-stage gastric cancer.

2.9 Authors : P. Bhardwaj, S. Kumar and Y. Kumar

Title : Deep Learning Techniques in Gastric Cancer Prediction and Diagnosis

This project addresses the growing concern of gastric cancer, which ranks as the fourth leading cause of cancer-related deaths worldwide. It reviews the current methods for detecting gastric cancer and examines various contributing risk factors. The study also evaluates global incidence and mortality rates associated with the disease.

The research highlights the use of machine learning and deep learning techniques in detecting gastric cancer, assessing their effectiveness and potential applications. The comparative analysis suggests that while current AI-based detection systems show promise, there is still a need to enhance their accuracy and early detection capabilities. Early diagnosis is crucial in preventing the disease's progression and reducing its severity.

2.10 Authors : Teramoto A, Shibata T, Yamada H, Hirooka Y, Saito K, Fujita

Title : Detection and Characterization of Gastric Cancer Using Cascade Deep Learning Model in Endoscopic Images.

This project introduces a cascaded deep learning approach to enhance the detection and classification of gastric cancer from endoscopic images. Traditional endoscopic examinations require extensive expertise, particularly when analyzing lesions in real-time. In prior research, direct segmentation of invasive areas was performed but resulted in challenges like high false positives and computational costs. The proposed solution addresses these issues by first classifying images into normal, early-stage, or advanced gastric cancer using a convolutional neural network (CNN), followed by segmentation of invasive regions using two U-Net models for cancer-identified images.

The model was evaluated on a dataset of 1,208 healthy images, 533 images of early gastric cancer, and 637 of advanced cancer. In a case-based evaluation, both sensitivity and specificity were 100%. The approach accurately distinguished normal from cancerous images and identified the depth of cancer invasion, with minimal false positives. These results suggest that this cascaded model is effective for automated endoscopic screening, offering precise detection and assessment of gastric cancer.

2.11 Authors : Zhao, Y., Hu, B., Wang, Y. ***et al.***

Title : Identification of gastric cancer with convolutional neural networks: a systematic review.

This project explores the use of convolutional neural networks (CNNs) for identifying gastric cancer through medical imaging. A systematic review was conducted, examining 27 studies from databases like Embase, Cochrane Library, PubMed, and Web of Science. The studies utilized CNNs to analyze both endoscopic and pathological images, with 19 focusing on endoscopic images and 8 on pathological samples. The research covered various aspects, including cancer detection, classification, segmentation, and delineation of cancer margins, employing CNN models like AlexNet, ResNet, VGG, Inception, and DenseNet.

The studies demonstrated high accuracy rates, ranging from 77.3% to 98.7%. The findings indicate that CNNs are highly effective in identifying gastric cancer and can significantly enhance diagnostic accuracy. As a result, CNN-based systems are expected to assist doctors and pathologists in making quicker and more accurate diagnoses, thereby improving clinical outcomes.

2.12 Authors: Du, H., Yang, Q., Ge, A. *et al.*

Title: Explainable machine learning models for early gastric cancer diagnosis.

This project focuses on using explainable machine learning models to improve the early diagnosis of gastric cancer, which is particularly prevalent in East Asia. By evaluating various models like WeightedEnsemble, CatBoost, and RandomForest, the study demonstrated high diagnostic accuracy in identifying early-stage gastric cancer. The emphasis on model explainability is crucial, as it increases trust and acceptance among clinicians by allowing them to understand the decision-making process. The research highlights the significance of identifying key biomarkers and clinical features, enhancing diagnostic accuracy and providing insights into the disease's pathophysiology.

The study’s integration of explainable techniques significantly boosted the transparency and reliability of machine learning predictions, especially through the WeightedEnsemble model. The methods developed here are versatile and can be applied to other medical diagnostics, optimizing early detection and treatment strategies. Future work will explore advanced techniques like attention mechanisms and expand datasets to improve model generalization. By enhancing both the explainability and predictive capabilities of machine learning models, this research not only improves medical decision-making but also drives forward innovations in clinical practices and medical technologies.

CHAPTER-3

PROPOSED METHODOLOGY

3.1 EXISTING SYSTEM:

- **Methodology:**Utilizes MATLAB algorithms to enhance image quality, remove noise, and eliminate artifacts like reflected flash spots.
- **Filters used:**Weighted Guided Filter (WGF),InpaintExemplar function (2 filters).
- **Algorithms-used:**YOLOv5,Histogram-Equalization,Saliency Weightmap(3 algorithms)

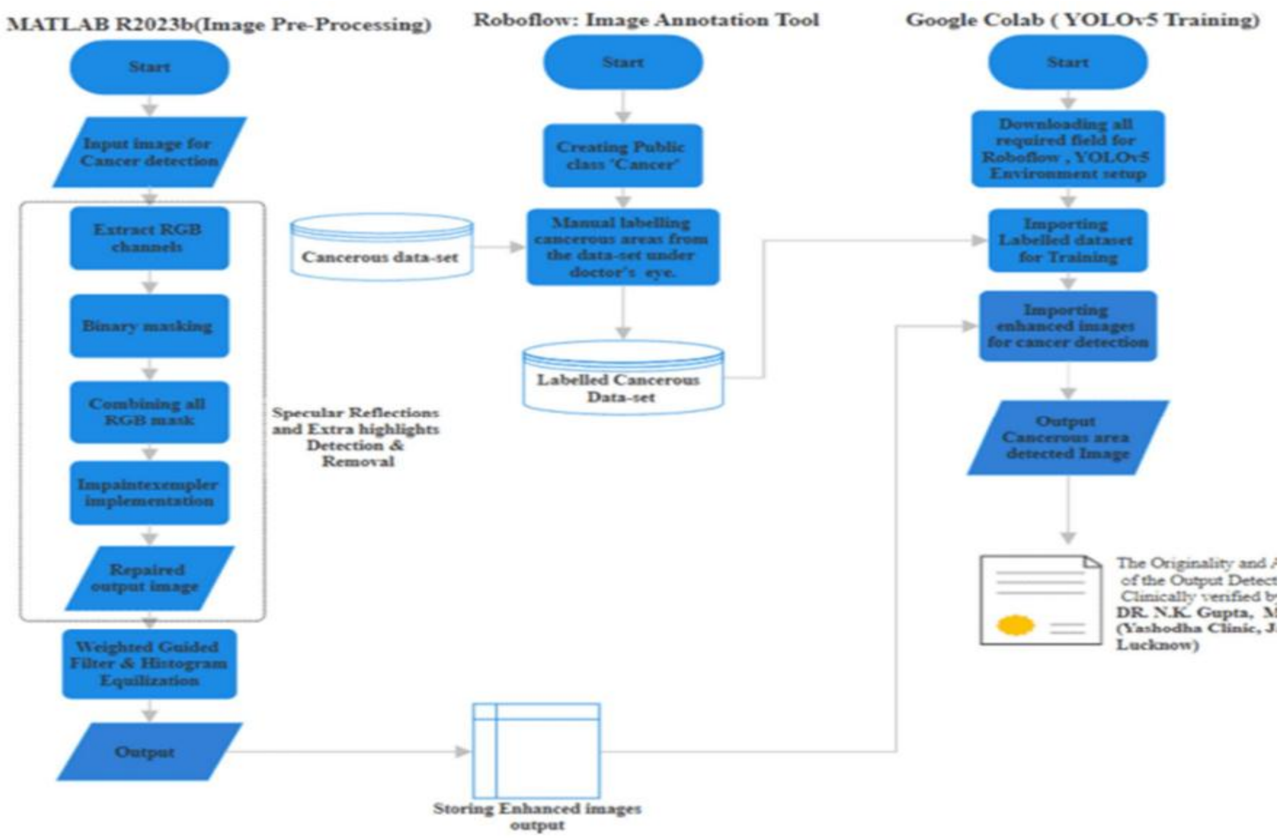

Fig.3.1 Block Diagram for existing system

3.1.1 Drawbacks:

- **Manual Annotation:** Time-consuming and prone to human error.
- **Limited Dataset Generalization:** The model may not generalize well across diverse datasets.
- **Artifact Handling:** While noise and reflections are reduced, some artifacts still affect image quality and analysis.
- Dependency on Expert Intervention

3.2 Proposed System :

- **Methodology:**The methodology begins with image acquisition, followed by contrast enhancement using histogram stretching and RGB-to-grayscale conversion for simplified processing. To reduce noise, Gaussian and median filters are applied, and edges are detected with the Canny method. The image is converted to HSV color space to analyze individual channels, then enhanced through morphological operations. K-means clustering is applied for color-based segmentation, grouping pixels by clusters.Key features are extracted with Discrete Wavelet Transform (DWT), and Principal Component Analysis (PCA). Finally, a Convolutional Neural Network (CNN) classifier uses these features for pattern recognition and prediction.
- **Algorithms used:**RGB extraction,Converting to grayscale,Smooth filter,Binary mask,Histogram.
- **Filters used:**Gaussian Filter,Median Filter,Edge Preserving Filter,Morphological Filters.
- **Techniques:**Segmentation,k-means clustering.

METRICS	POLYPS	GI BLEEDING	ULCER	NORMAL
CONTRAST	0.1922-0.3420	0.2105-0.2956	0.1980-0.4235	0.2130-0.3026
CORRELATION	0.0735-0.1799	0.0648-0.1702	0.0381-0.1850	0.0323-0.1664
ENERGY	0.7222-0.8265	0.7407-0.8045	0.7364-0.8512	0.7356-0.8042
MEAN	0.0014-0.0057	0.0020-0.0058	0.0019-0.0064	0.0015-0.0052
STANDARD DEVIATION	0.0896-0.0898	0.0896-0.0898	0.0896-0.0898	0.0897-0.0898
ENTROPY	2.3894-3.7168	2.8284-3.6029	2.3247-3.6861	2.9682-3.7423
RMS	0.0898	0.0898	0.0898	0.0898
VARIANCE	0.0080-0.0081	0.0080-0.0081	0.0080-0.0081	0.0080
KURTOSIS	4.1223-	6.2727-13.8553	5.5237-28.4905	5.2114-12.1648
SKEWNESS	0.3358-1.9725	0.3326-1.1057	0.3927-2.6899	0.4322-1.2595

Table 3.2.1 Disease identification features and ranges according to Conditions

These are the disease identification features.we did a research on values which they fall under each Conditions such as Polyps.GI Bleeding,Ulcer,Normal Stages. They most likely depend on the images's quality and intensity so we can obtain the approximate values of range that they fall into.This research will be much helpful to crosscheck and analyse particular condition by their feature's values.

3.3. Description of features:

Contrast: A measure of the intensity difference between a pixel and its neighbors over an image, indicating the level of variation.

Correlation: Describes the linear relationship between pixel intensities, showing how similar pixel patterns are within an image.

Energy: Represents the sum of squared pixel values, indicating texture uniformity; higher energy suggests less texture complexity.

Mean: The average intensity value across all pixels in an image, giving a measure of brightness.

Variance: A measure of intensity variability in an image, showing how much pixel values differ from the mean.

Standard Deviation: The square root of variance, indicating the spread or dispersion of intensity values around the mean.

Kurtosis: Measures the "tailedness" of the pixel intensity distribution, with higher kurtosis indicating more intense peaks.

Skewness: Describes the asymmetry of the intensity distribution; positive or negative skewness indicates an uneven spread of values.

Entropy: Reflects the randomness in pixel intensities, with higher entropy indicating more texture complexity.

Root Mean Square (RMS): The square root of the average of squared pixel intensities, used as an indicator of overall image intensity.

3.4 Advantages:

- **Automating Feature Extraction:** Instead of relying heavily on manual marking, It will employ advanced algorithms to automate the detection and extraction of significant features from endoscopic images, reducing human error and time consumption.
- **Improved Noise Removal:** The system will integrate advanced noise removal techniques to ensure that even the finest details of the medical images are preserved, leading to higher accuracy in diagnosis.
- **Enhanced Detection Algorithms:** Introduce improved detection algorithms, offering more precise differentiation between cancerous and non-cancerous areas. This could include better handling of specular reflections and minimizing artifacts that affect image clarity.
- **Real-time Processing:** The system will focus on improving the speed of image analysis and feature extraction, making it more suitable for real-time medical applications.
- **Broader Dataset Integration:** By using a more diverse and comprehensive dataset,The system will aim to provide better generalization across different cases, making it more reliable in clinical settings.

3.5 Block Diagram Description:

Input Image: The process begins with an input image of the gastrointestinal tract, typically obtained from medical imaging devices such as endoscopy or MRI.

RGB to Gray Conversion: The image is converted from RGB to grayscale to simplify processing and reduce computational complexity, as grayscale images retain essential information needed for analysis.

Gaussian Filter: A Gaussian filter is applied to the grayscale image to remove noise and smooth out the image, which helps in enhancing the overall clarity and reducing minor irregularities that could affect further processing steps.

Median Filter: After Gaussian filtering, a median filter is applied to reduce salt-and-pepper noise and preserve edges. This filter improves image quality without blurring the key features, which is important for accurate detection of fine structures.

Edge Detection: Edges in the filtered image are detected to highlight boundaries and regions of interest, helping to distinguish features that may indicate abnormal areas in the gastrointestinal tract.

High Saturation Value: Saturation adjustments are made to enhance specific regions in the image. High saturation values increase the visibility of certain features, making it easier to identify patterns associated with potential diseases.

Enhancement: Further enhancement techniques are applied to improve image quality, contrast, and visibility, ensuring that the critical features are clearly distinguishable for accurate analysis.

Segmentation: The enhanced image undergoes segmentation to isolate regions of interest, such as lesions or abnormal tissue areas, allowing the system to focus on these specific parts for feature extraction and classification.

Feature Extraction: Key features are extracted from the segmented regions, such as texture, shape, and intensity, which provide valuable data for the classification model.

Trained Data: The extracted features are compared with previously trained data, which contains labeled examples of both healthy and diseased tissue. This trained dataset serves as a reference for classification.

CNN Classification: A Convolutional Neural Network (CNN) is used for classification, leveraging its ability to recognize patterns and classify the input based on the extracted features. CNNs are effective in identifying complex features and differentiating between healthy and diseased tissue.

Disease Identification Output: The final output indicates whether the input image shows signs of disease, providing diagnostic insights that can aid in further medical examination and treatment planning.

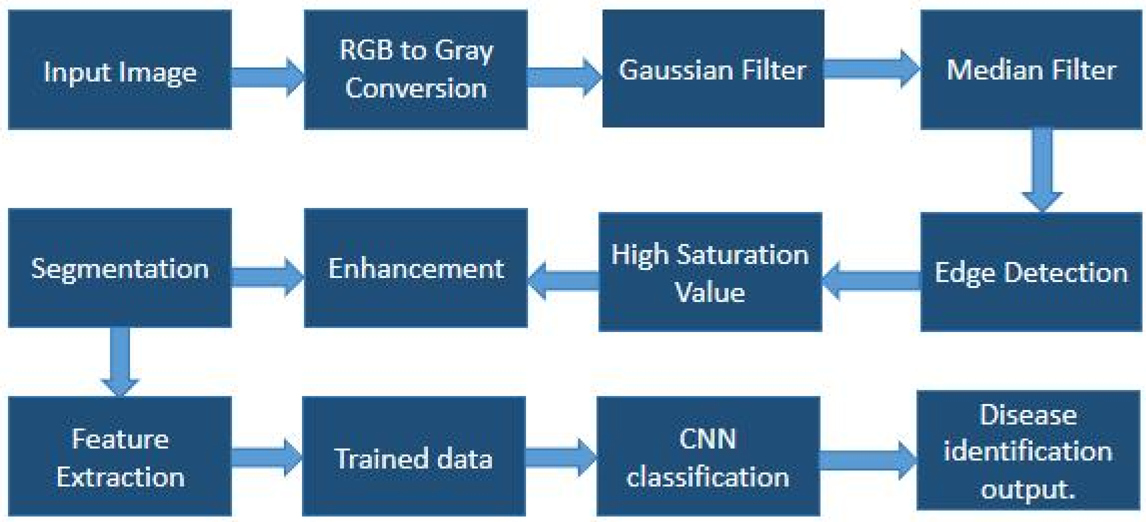

Fig.3.5.1 Block Diagram

3.6 Polyps,Ulcer,GI Bleeding,Normal Stage Image Acquisition:

In this project, image acquisition involves obtaining a dataset of gastrointestinal images from the Kaggle-Kvasir dataset. The Kvasir dataset provides a diverse collection of endoscopic images, including cases of polyps, ulcers, GI bleeding, and normal stages of the gastrointestinal tract. These high-quality, labeled images serve as a reliable foundation for training and testing the model, ensuring it learns to identify specific features associated with each condition. The use of this dataset enables the model to distinguish between healthy tissue and abnormalities with precision, enhancing the accuracy and robustness of disease detection. By leveraging real-world images from the Kvasir dataset, our project simulates a practical diagnostic setting, making the model highly relevant for clinical applications.

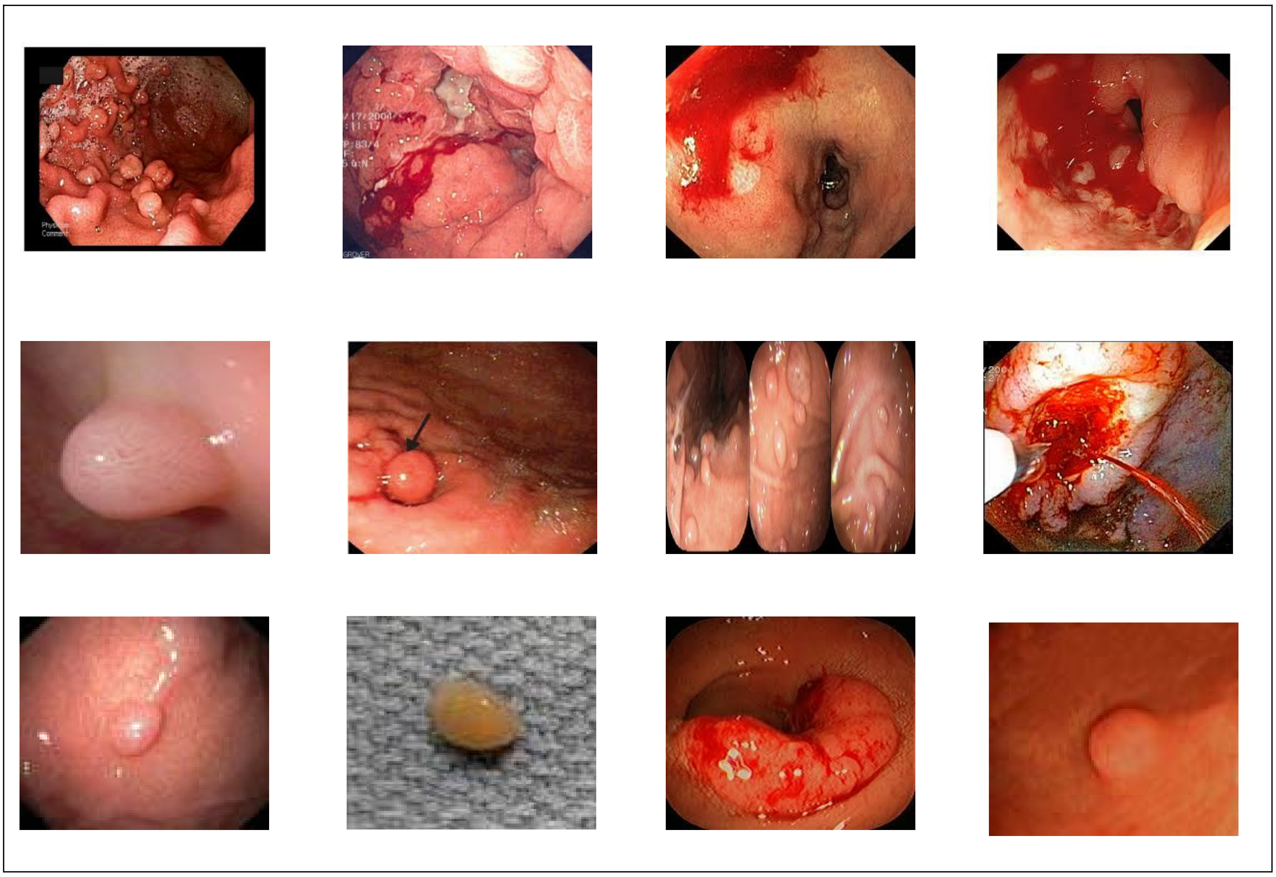

Fig.3.6.1 optical images of stomach diseases

These are some of the sample dataset images , We collected 250 images totally which comprises of Polyps, Ulcer,GI bleeding, Normal Stage images for training the model.

3.7 IMAGE PROCESSING:

In this project, image processing plays a critical role in enhancing the accuracy of gastrointestinal disease detection. By applying a series of preprocessing steps, such as RGB to grayscale conversion, Gaussian filtering, and median filtering, we ensure that the images are clean, noise-free, and well-suited for analysis. These steps improve clarity, allowing key features of the GI tract, like lesions or abnormal tissue, to stand out. Additional techniques, such as edge detection and contrast enhancement, further highlight essential details, making it easier for the model to identify patterns associated with polyps, ulcers, GI bleeding, and normal stages. This meticulous preprocessing enhances the quality of input data, making subsequent stages like feature extraction and classification more effective and accurate.

Image processing for gastrointestinal disease detection comes with its own set of challenges. Variations in lighting, noise, and image quality across different endoscopy devices can make standardization difficult. Additionally, gastrointestinal structures have complex shapes, textures, and overlapping features that can be hard to distinguish, especially in cases of minor lesions or subtle bleeding. Another challenge lies in differentiating between abnormalities and normal variations in tissue, as some benign features may resemble disease-related patterns. Balancing image enhancement without introducing artifacts is crucial, as excessive filtering or enhancement may obscure important details. These challenges necessitate careful tuning of image processing techniques to achieve reliable results in a variety of imaging conditions.

Segmentation is a key step in this project, isolating regions of interest within each image for focused analysis. By dividing the image into meaningful sections, segmentation allows the model to concentrate on specific areas, such as potential polyps or ulcerated regions, which significantly improves detection accuracy. This targeted approach reduces the noise and irrelevant information, making feature extraction more precise and allowing for detailed analysis of the segmented regions. Proper segmentation also supports the CNN in classifying diseases accurately, as the model only processes the essential parts of the image, leading to faster processing and better diagnostic efficiency. In this project, segmentation is fundamental to achieving a high level of detail in disease detection.

3.7.1 Gray scale conversion

Grayscale conversion is used to simplify and standardize images by reducing them to shades of gray, where each pixel's intensity represents its brightness. It eliminates color variations, making images more amenable to analysis and efficient for various applications. This process enhances the visibility of image details, emphasizes texture, and is particularly valuable in fields like medical imaging, computer vision, and photography, where color may not be as relevant as the intensity or contrast in the image. Grayscale images are also more compact, making them easier to store and process, and they are compatible with a wide range of image processing techniques and algorithms.

In this project, grayscale conversion is an essential preprocessing step that simplifies the analysis of gastrointestinal images by reducing them from three color channels (RGB) to a single intensity channel. This transformation not only reduces computational complexity but also enhances important structural features, such as the edges and textures associated with polyps, ulcers, and bleeding areas. By focusing on intensity rather than color, grayscale images allow subsequent processing steps, like filtering and edge detection, to be more efficient and effective, ultimately contributing to improved feature extraction and disease classification accuracy in the CNN model.

Secondly, grayscale conversion reduces data size, making the images more manageable and efficient for storage and processing.

Grayscale conversion is a straightforward process that doesn't involve a specific mathematical formula. Instead, it's a method of transforming a color image into a grayscale image, typically by taking the average of the color channels (red, green, and blue) to determine the intensity value of each pixel.

simple formula for grayscale conversion:

$$\text{Grayscale Value} = (R + G + B) / 3$$

In this formula:

- ‘R’ represents the red channel value of the pixel.
- ‘G’ represents the green channel value of the pixel.
- ‘B’ represents the blue channel value of the pixel.

  This formula calculates the average of the three color channels, resulting in a grayscale value for each pixel. However, in some cases, variations of this formula may be used, such as giving different weights to the channels (e.g., using $0.299R + 0.587G + 0.114B$, which mimics the human perception of color) to create more visually pleasing grayscale images.

Original Image **Gray Scaled Image**

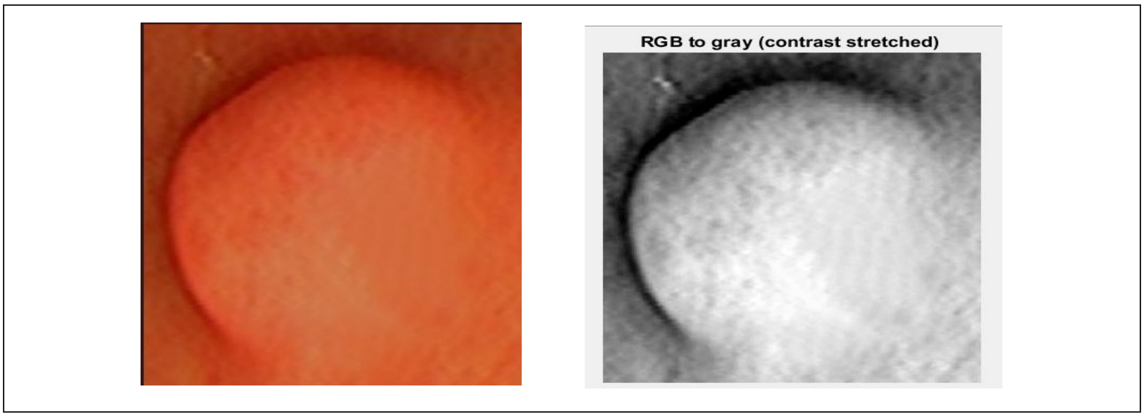

Fig.3.7.1 Gray Scaled Image

3.7.2 Gaussian Filter:

the Gaussian filter is applied to smooth gastrointestinal images by reducing noise and unwanted variations that may interfere with accurate feature extraction. The Gaussian filter works by averaging the pixel values in a localized area around each pixel, using a weighted distribution where closer pixels have a higher influence. This process softens minor details and irregularities in the image, making significant structures, such as lesions or abnormal textures, more prominent. By reducing high-frequency noise, the Gaussian filter enhances the clarity of essential features, which improves the effectiveness of subsequent processing steps, such as edge detection and segmentation. This filtering ultimately contributes to more precise classification by the CNN model, as it allows the network to focus on relevant features without distractions from noise or artifact

Original Image **Gaussian Filtered Image**

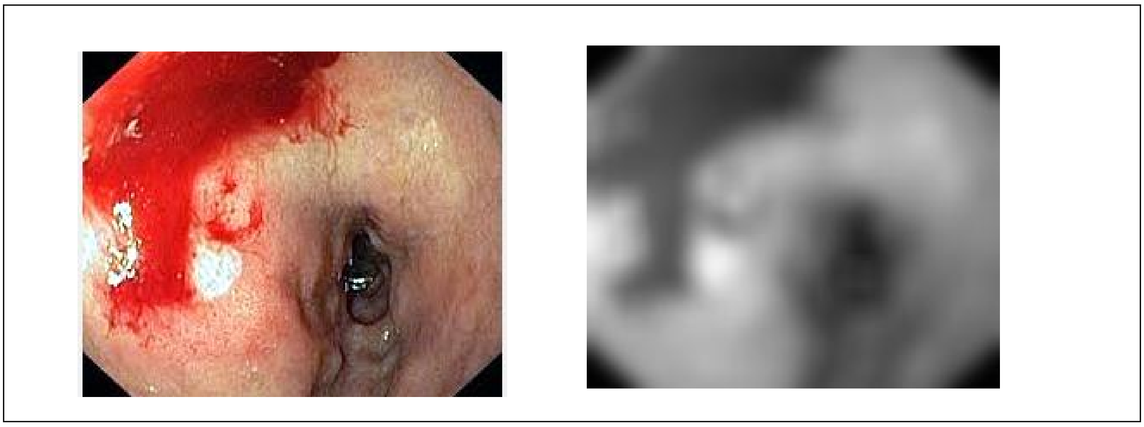

Fig.3.7.2 Gaussian filtered Image

3.7.3 Noise Reduction :

In this project, noise reduction is a crucial preprocessing step to enhance image quality and improve disease identification accuracy in gastrointestinal (GI) diagnostics. The diagram shows a workflow where the input image first undergoes RGB to grayscale conversion, followed by the application of both Gaussian and median filters. Gaussian filtering helps to reduce high-frequency noise by smoothing the image, effectively diminishing random variations in pixel intensities while preserving essential image features. This process helps to eliminate visual clutter that could interfere with subsequent steps.

After Gaussian filtering, the median filter is applied to further suppress noise, especially impulse noise (salt-and-pepper noise), which can affect diagnostic clarity. Unlike Gaussian filtering, the median filter is adept at preserving edges while removing outlier noise, making it ideal for medical images where edge definition is important for feature extraction. By integrating these two filtering techniques, the system achieves a cleaner, more accurate image that is better suited for edge detection, segmentation, and further processing.

3.7.4 Median Filter :

the median filter plays a vital role in refining the image by effectively reducing impulse noise, such as salt-and-pepper noise, which commonly appears in medical imaging. Unlike linear filters, the median filter operates by replacing each pixel value with the median value of the pixels within a defined neighborhood. This approach preserves edges and important structural details while smoothing out noise, making it particularly suitable for images where maintaining edge clarity is essential for subsequent feature extraction and analysis. By using the median filter after the Gaussian filter, this project ensures a cleaner, more reliable image input for segmentation and classification, ultimately enhancing the accuracy of disease identification in gastrointestinal diagnostics.

3.7.5 EDGE DETECTION:

Edge detection is an image processing technique used to identify and highlight the boundaries or edges of objects within an image. It is employed in image segmentation to enhance the detection of object contours, which aids in separating different regions or objects of interest in an image. Edge detection is valuable for several reasons:

1. Object Separation: By identifying edges or boundaries within an image, edge detection helps distinguish objects or regions from the background. This separation is a fundamental step in image segmentation, allowing for the isolation of specific features or objects within the image.

2. Feature Extraction: Edge detection is crucial for extracting important features or details within an image, such as the outline of an object or the transition between different regions. These extracted features can be used for subsequent analysis or measurements.

3. Enhanced Image Understanding: Detecting edges provides a better visual representation of the image structure. It helps reveal the overall shape and geometry of objects, making it easier for human interpretation and computer-based analysis.

4. Object Recognition: Once the edges are detected, further processing can be performed to recognize and classify objects within the image, which is a common goal in image segmentation and object recognition tasks.

Common edge detection techniques include the Sobel operator, Canny edge detector, and the Prewitt operator, among others. These methods analyze the intensity variations between neighboring pixels to locate significant changes that indicate the presence of an edge. Edge detection is a crucial step in image segmentation as it contributes to the accurate and effective separation of objects or regions in digital images, supporting a wide range of applications in fields like computer vision, medical imaging, and pattern recognition.

In this project context, edge detection plays a critical role in identifying and delineating the boundaries of key structures within the gastrointestinal images. After noise reduction using Gaussian and median filters, edge detection is applied to highlight the contours of regions of interest, such as abnormal tissues or lesions. This step enhances the distinction between Normal and potentially diseased areas such as Polyps, GI-Bleeding , Ulcer-abnormal areas enabling more precise segmentation.

The contribution of edge detection to this project lies in its ability to simplify the complex visual information in the input images by isolating essential structural details. This, in turn, aids in focusing the feature extraction process on relevant areas, improving the performance of the CNN classification model by reducing distractions from irrelevant background information. As a result, the system achieves more accurate disease identification, enhancing diagnostic reliability and supporting clinicians in the effective analysis of gastrointestinal pathologies

Original Image **Edge Detected Image**

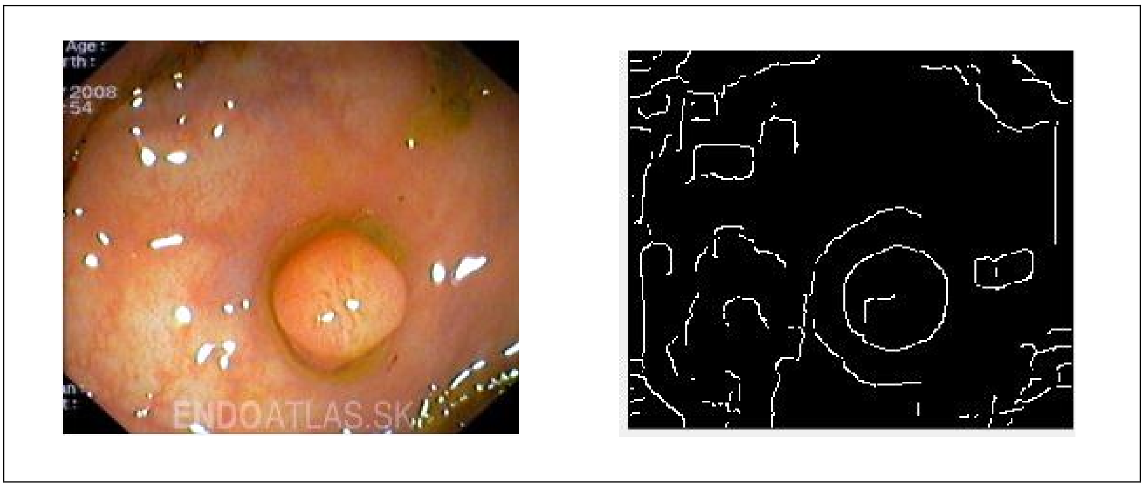

Fig. 3.7.3 Edge detected image

3.7.6 Binary Conversion of Adjusted Gray Image:

In the context of our project, binary conversion is applied to the adjusted grayscale image to create a clear, high-contrast black-and-white representation. This conversion helps in distinguishing between different regions by separating areas of interest (like potential disease regions) from the background. By converting the grayscale image into binary, the project emphasizes structures in the gastrointestinal images, allowing for easier identification of abnormalities. This binary conversion process essentially simplifies the image by reducing it to two pixel values (0 and 1), which aids in further processing steps. We gave a threshold value as 0.5 which means the pixels which have above 0.5 intensity value will be represented as white and the pixels which are equal or below 0.5 intensity will be represented as black in binary image.

Following binary conversion, a complement operation is performed on the black-and-white image to invert the pixel values. This step is crucial because it reverses the image such that areas of interest, which were previously black, now appear white, and vice versa. This transformation makes it easier to detect and analyze features of interest in the subsequent steps. Complementing the image enhances the visual contrast, making abnormalities more distinct and enabling a more accurate extraction of key regions.

The final step involves applying morphological operations to the complemented black-and-white image. Specifically, operations like dilation and closing are used to fill any small holes or gaps within the detected regions, creating a more cohesive structure in the binary image. These operations help remove noise, connect disjointed elements, and create solid, continuous areas that are easier for the feature extraction and classification stages to process. The morphological filling of holes ultimately contributes to a more precise and reliable classification by the CNN, enhancing the accuracy of disease identification in the endoscopic images.

Fig.3.7.4 Binary Converted and Dilated

3.7.7 Enhancement:

an RGB image is split into its individual color channels: red (redBand), green (greenBand), and blue (blueBand). Each channel is isolated from the original image, allowing for independent enhancement or analysis of specific color bands. The code then displays each channel separately using (imshow) in three different figures, with titles "ENCHANCEMENT_1","ENCHANCEMENT_2","ENCHANCEMENT_3" for the red, green, and blue channels respectively. The font size for each title is set to 10, ensuring consistent labeling for easy identification of each enhanced color band. This breakdown can be useful for highlighting specific features or patterns within each color component of the image.

Fig.3.7.5 Enhancements of RGB Bands

3.7.8 Segmentation :

In this project, segmentation is performed to isolate different regions of interest within the image, helping in the detailed analysis of specific tissue features for disease diagnosis. We applied the **k-means clustering technique** to segment the image based on color similarities, separating it into three distinct color clusters. By clustering similar colors, this method effectively differentiates various regions, which is particularly useful for identifying patterns or abnormalities in tissue. The segmentation process 4.8through k-means clustering enhances the clarity of specific features by grouping similar pixel colors, making it easier to focus on particular areas relevant to identifying and classifying gastrointestinal conditions. This segmentation approach is crucial as it improves the accuracy of feature extraction and disease classification in subsequent stages of our automated analysis system.

We got color based and non color based segmentation results,

Color-Based Segmentation: The images labeled "color based segment" and "segmentation" showcase color-based segmentation. In these steps, the segmentation relies on differentiating regions based on color. This is likely achieved through a technique like k-means clustering, where distinct colors are separated to isolate the region of interest from the background. This technique is especially useful when the target area has a unique color that can be easily separated from other regions.

Non-Color-Based Segmentation: The image labeled "800 Iterations" appears to represent a non-color-based segmentation result. In this step, boundary detection (perhaps through an iterative process like active contours or edge detection) highlights the shape of the region of interest without relying on color. Instead, it uses contrast or intensity changes to detect edges and separate the target area.

This combination of color-based and non-color-based segmentation enhances the accuracy, allowing the segmentation process to effectively capture both the general and detailed shapes of the region of interest.

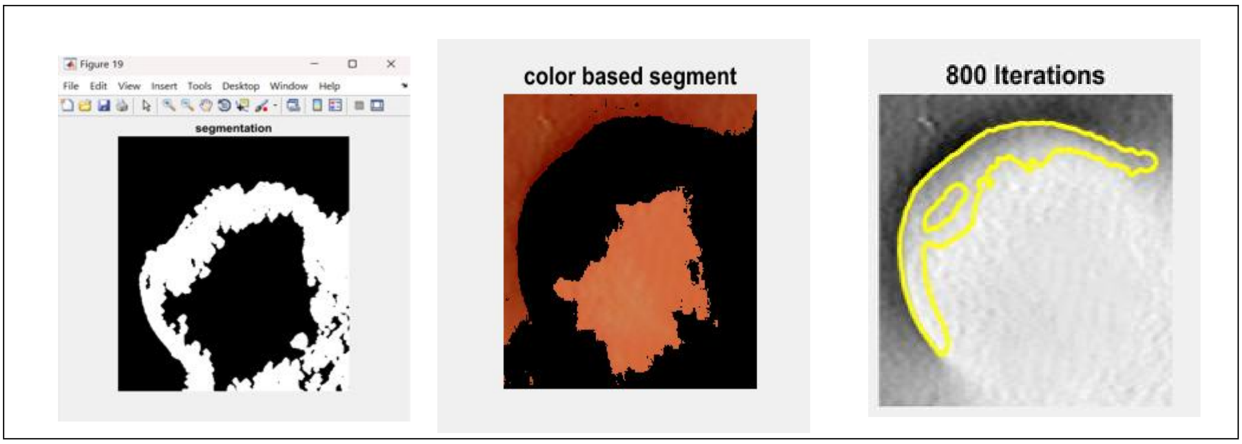

Fig.3.7.6 Segmentation

The distance is calculated by Euclidean Distance Metric calculates the straight-line distance between two points in space, often used to measure similarity in various applications like image processing and clustering.

Given two points (x1,y1)(x_1, y_1)(x1,y1) and (x2,y2)(x_2, y_2)(x2,y2), the Euclidean distance d is determined by the formula:

d=(x2−x1)2+(y2−y1)2d=\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}d=(x2−x1)2+(y2−y1)2

In this project, it helps to assess spatial closeness, such as differentiating between clusters in segmented images by calculating distances between pixel intensities or features.

3.8 Feature Extraction :

3.8.1 2D Discrete Wavelet Transform (DWT)

Function: dwt2(signal1, 'db4')

- **Purpose**: Applies the 2D Discrete Wavelet Transform (DWT) on signal1 using the Daubechies wavelet with a 4-tap filter (db4).
- **Output Components**:
  - **cA**: Approximation coefficients (low-frequency information).
  - **cH**: Horizontal detail coefficients (horizontal high-frequency information).
  - **cV**: Vertical detail coefficients (vertical high-frequency information).
  - **cD**: Diagonal detail coefficients (diagonal high-frequency information).

The **DWT is applied three times** iteratively on the approximation coefficients (cA) from the previous level, extracting detail at multiple scales.

3.8.2 Principal Component Analysis (PCA)

Function: G = pca(DWT_feat)

- **Purpose**: Reduces the dimensionality of the DWT coefficients and extracts essential features.
- **Output**: G contains the **principal components** derived from the wavelet features, which represent the most important variations within the data.

3.8.3 GLCM Statistical Properties:

Function: graycoprops(g, 'Contrast Correlation Energy Homogeneity')

This function computes several statistical properties based on the **Gray-Level Co-occurrence Matrix (GLCM)**:

- **Contrast**: Measures the intensity contrast between a pixel and its neighbor across the whole image.
- **Correlation**: Indicates how correlated a pixel is with its neighbor.
- **Energy**: Reflects the uniformity or energy in the image.
- **Homogeneity**: Measures how close the distribution of elements in the GLCM is to its diagonal, indicating uniformity.

Statistical Features of PCA Result

These statistical measures provide insights into the **characteristics of the PCA-transformed data**:

- **Mean**: Average value of the PCA-transformed pixel intensities.
- **Standard Deviation**: Dispersion of the pixel intensities around the mean.

- **Entropy**: Reflects the amount of information or complexity in the image.
- **RMS (Root Mean Square)**: Indicates the overall energy of the pixel values.
- **Variance**: Measures the deviation of pixel values from the mean.
- **Smoothness**: Represents the smoothness of the image, based on the sum of pixel values.
- **Kurtosis**: Quantifies the "tailedness" of the intensity distribution.
- **Skewness**: Measures the asymmetry in the intensity distribution.

3.9 Histogram:

A histogram is a graphical representation of the distribution of numerical data. It displays the frequency of data points within specified ranges, known as bins, on the x-axis, while the y-axis shows the count or proportion of data points that fall into each bin. Histograms are commonly used in statistics and data analysis to visualize the underlying frequency distribution of a dataset, making it easier to identify patterns, trends, and anomalies.

In the context of our project, histograms play a crucial role in analyzing the distribution of pixel intensities in the processed medical images. By plotting the histogram of an image, we can visually assess how pixel values are distributed, which aids in understanding the overall brightness, contrast, and quality of the image. This information is essential for applying appropriate image enhancement techniques, such as contrast stretching or histogram equalization, to improve the visibility of important features related to disease detection.

CHAPTER-4
SOFTWARE AND REQUIREMENTS

4.1. SYSTEM REQUIREMENTS FOR MATLAB

- Windows 10
- Windows 8.1
- Windows 8
- Windows 7 Service Pack 1
- Windows Server 2016
- Windows Server 2012
- Windows Server 2008 R2 Service Pack 1
- Processors
- Any Intel or AMD x86-64 processor.
- Disk Space:
- 2 GB for MATLAB only,
- 4–6 GB for a typical installation.
- RAM
- 2 GB
- No specific graphics card is required.

4.2. MATLAB

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Typical uses include:

•Math and computation

•Algorithm development

•Modeling, simulation, and prototyping

•Data analysis, exploration, and visualization

•Scientific and engineering graphics

•Application development, including graphical user interface building

MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar noninteractive language such as C or Fortran.

The name MATLAB stands for matrix laboratory. MATLAB was originally written to provide easy access to matrix software developed by the LINPACK and EISPACK projects. Today, MATLAB uses software developed by the LAPACK and ARPACK projects, which together represent the state-of-the-art in software for matrix computation. MATLAB has evolved over a period of years with input from many users. In university environments, it is the standard instructional tool for introductory and advanced courses in mathematics, engineering, and science. In industry, MATLAB is the tool of choice for high-productivity research, development, and analysis.

4.3 Toolboxes

MATLAB features a family of application-specific solutions called *toolboxes*. Very important to most users of MATLAB, toolboxes allow you to learn and apply specialized technology. Toolboxes are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve classes of problems. Areas in which toolboxes are available include signal processing, control systems, neural networks, fuzzy logic, wavelets, simulation, and many others.

4.4 The MATLAB System

The MATLAB system consists of five main parts:

4.4.1 Development Environment.

This is the set of tools and facilities that help you use MATLAB functions and files. Many of these tools are graphical user interfaces.

It includes the MATLAB desktop and Command Window, a command history, and browsers for viewing help, the workspace, files, and the search path.

4.4.2 The MATLAB Mathematical Function Library.

This is a vast collection of computational algorithms ranging from elementary functions like sum, sine, cosine, and complex arithmetic, to more sophisticated functions like matrix inverse, matrix eigenvalues, Bessel functions, and fast Fourier transforms.

4.4.3 The MATLAB language.

This is a high-level matrix/array language with control flow statements, functions, data structures, input/output, and object-oriented programming features. It allows both “programming in the small” to rapidly create quick and dirty throw-away programs, and “programming in the large” to create complete large and complex application programs.

4.4.4 Handle Graphics.

This is the MATLAB graphics system. It includes high-level commands for two-dimensional and three-dimensional data visualization, image processing, animation, and presentation graphics. It also includes low-level commands that allow you to fully customize the appearance of graphics as well as to build complete graphical user interfaces on your MATLAB applications.

4.4.5 The MATLAB Application Program Interface (API).

This is a library that allows you to write C and Fortran programs that interact with MATLAB.

It includes facilities for calling routines from MATLAB (dynamic linking), calling MATLAB as a computational engine, and for reading and writing MAT-files.

4.4.6 Image processing in MATLAB

Images and pictures. As we mentioned in the preface, human beings are predominantly visual creatures: we rely heavily on our vision to make sense of the world around us. We not only look at things to identify and classify them, but we can scan for differences, and obtain an overall rough _feeling_ for a scene with a quick glance. Humans have evolved very precise visual skills: we can identify a face in an instant; we can differentiate colours; we can process a large amount of visual information very quickly.

However, the world is in constant motion: stare at something for long enough and it will change in some way. Even a large solid structure, like a building or a mountain, will change its appearance depending on the time of day (day or night); amount of sunlight (clear or cloudy), or various shadows falling upon it.

We are concerned with single images: snapshots, if you like, of a visual scene. Although image processing can deal with changing scenes, we shall not discuss it in any detail in this text.

For our purposes, an image is a single picture which represents something. It may be a picture of a person, of people or animals, or of an outdoor scene, or a microphotograph of an electronic component, or the result of medical imaging. Even if the picture is not immediately recognizable, it will not be just a random blur.

What is image processing?

Image processing involves changing the nature of an image in order to either

1. improve its pictorial information for human interpretation,

2. render it more suitable for autonomous machine perception.

- Ø We shall be concerned with digital image processing, which involves using a computer to change the nature of a digital image .
- Ø It is necessary to realize that these two aspects represent two separates but equally important aspects of image processing.

4.4.7 Some applications:

- Medical Imaging: MATLAB is widely used for processing and analyzing medical images, including X-rays, MRI scans, and CT scans. It aids in tasks such as image enhancement, segmentation, and the detection of anomalies or tumors.
- Remote Sensing: MATLAB helps process satellite and aerial images for applications like land cover classification, climate monitoring, and disaster management.
- Object Detection and Recognition: MATLAB can be employed for object detection, tracking, and recognition in computer vision applications. This is useful in surveillance, autonomous vehicles, and robotics.
- Image Enhancement: Enhancing image quality through techniques like contrast adjustment, noise reduction, and sharpening is a common application. It's used in photography, forensics, and quality control.

CHAPTER-5
RESULT AND DISCUSSION

5.1 Output Images:

5.1.1 Enhancing Endoscopic Images Using RGB Band Separation

To improve the diagnostic accuracy of endoscopic images, this project utilizes a technique involving the separation of color bands—specifically, the red, green, and blue (RGB) channels. Each color band carries unique information that can highlight different aspects of the image. By isolating these channels, we can enhance specific features that may be obscured in the original composite image. For instance, the red channel is particularly effective in emphasizing areas with higher blood flow, which can help in detecting bleeding or identifying inflamed tissues. Meanwhile, the green and blue channels can reveal subtle textures and edges that may be critical for identifying abnormalities such as polyps or ulcers. This band separation approach is crucial for enhancing image clarity and ensuring that significant features are more discernible for further analysis.

In MATLAB, the separated channels are displayed as enhancement outputs labeled as Enhancement1, Enhancement2, and Enhancement3. These figures illustrate the effectiveness of processing each band individually, as each enhancement stage focuses on extracting specific details from the endoscopic images. By analyzing the images in these isolated color bands, our approach refines the visual information, making it easier for the Convolutional Neural Network (CNN) model to classify the conditions accurately. This method not only improves feature extraction but also reduces noise, leading to a higher degree of diagnostic precision. The enhanced images provide a clearer, more detailed view, allowing for better identification of early-stage gastric diseases and supporting more reliable diagnostic outcomes.

Fig.5.1.1 Enhanced Images

5.2 Edge Detection and Dilation results

In addition to color band separation, our project employs edge detection and dilation techniques to further enhance the quality of endoscopic images for accurate diagnosis. Edge detection is a critical step that identifies boundaries within an image, highlighting regions where there are significant changes in intensity. This technique is particularly useful in endoscopic imaging, as it helps outline the shapes and borders of abnormalities such as polyps, ulcers, and bleeding areas, making them more distinguishable from the surrounding tissue. The output of this process was displayed as an edge-detected image, where key structural features are clearly emphasized, aiding in more precise localization of potential disease areas.

Following edge detection, we applied dilation to the images to enhance the visibility of the identified features. Dilation is a morphological operation that enlarges the boundaries of detected edges, making subtle details more prominent. This process helps in reducing noise and filling in gaps, ensuring that the extracted features are continuous and easily recognizable. The dilated output, when displayed alongside the edge-detected image, provides a clearer and more refined representation of critical areas within the endoscopic images. By combining these enhancement techniques, we prepare the images for more effective analysis by the Convolutional Neural Network (CNN), ultimately improving the accuracy and reliability of our automated diagnostic system.

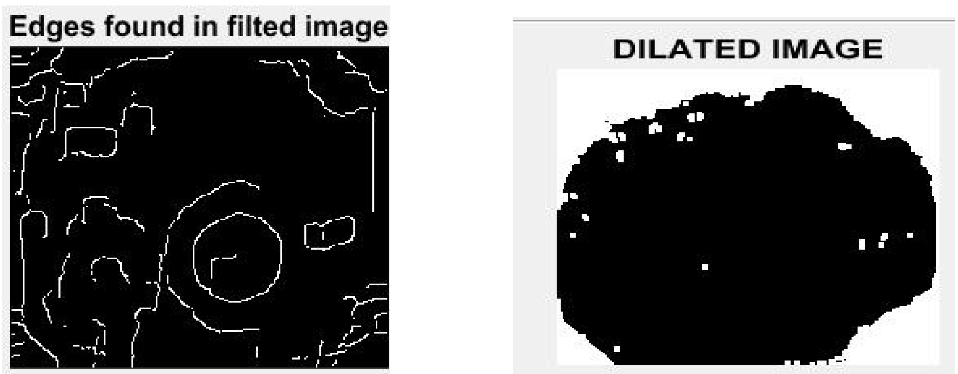

Fig.5.2.1 Edge Detected and Dilated Images

5.3 Segmentation Using K-Means Clustering for Enhanced Analysis results

To further refine the diagnostic process, our project employs segmentation using the K-means clustering algorithm, which groups similar pixels into clusters to distinguish different regions within the endoscopic images. This segmentation technique helps in isolating key areas, such as lesions, polyps, or abnormal tissues, making it easier to identify potential disease indicators. We displayed both colored and non-colored segmentation outputs, where the colored segmentation assigns distinct colors to different clusters, clearly highlighting the various regions of interest, while the non-colored segmentation focuses on enhancing contrast between the segmented areas. These segmented outputs enable a clearer distinction of abnormalities, improving the effectiveness of subsequent feature extraction and classification by the Convolutional Neural Network (CNN).

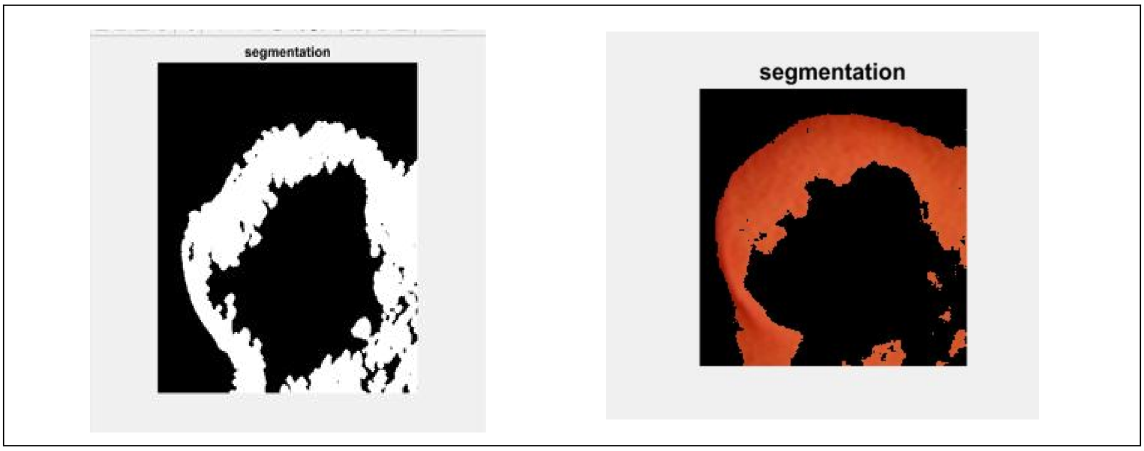

Fig.5.3.1 Segmented Images

5.4 Final Output in Dialog Box

The final result after completing the feature extraction , the disease is classified and displayed in a dialog box successfully with model's success rate of 99.2% accuracy indicates robust analysis.

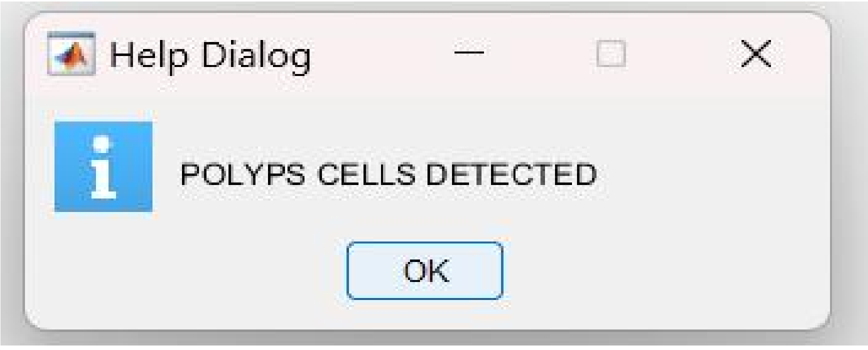

Fig.5.4.1 Help Dialog Box

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Accuracy of cnn with 800 iterations is: 99.2%
```

Fig. 5.4.2 Accuracy of model

5.5 Displaying Success Rate by Labels

To evaluate the performance of our diagnostic system, we displayed the success rates for each classified category using labels. These labels represent the four conditions—Polyp Cells Detection, Bleeding Identification, Normal Stage, and Ulcer Abnormal Stage—showing the system's accuracy in correctly identifying each condition. By visualizing the success rates, we demonstrate the effectiveness of our approach in achieving reliable classification, providing clear insights into areas of strength and potential improvement for further optimization. This analysis confirms the robustness of our model in supporting accurate diagnosis of gastrointestinal diseases.

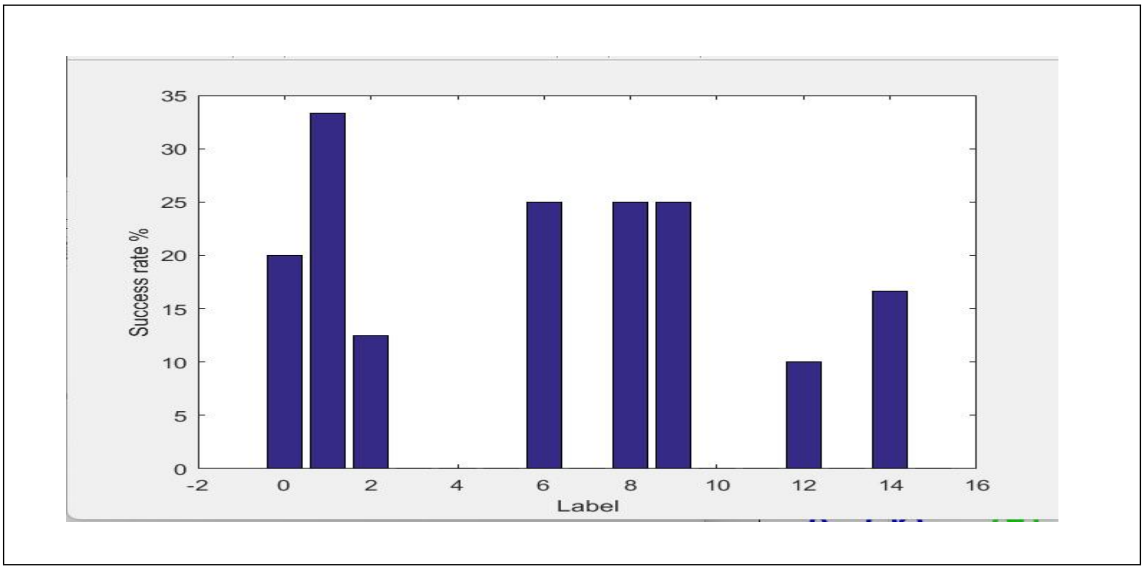

Fig.5.5.1 Success Rate by Labels

5.6 Success and Loss rate in Predictions

The image displays two plots illustrating the performance metrics of a predictive model across several training batches. The upper plot represents the classification success rate in percentage against the batch number, while the lower plot shows the loss values over the same batch range. In the classification plot, we observe that the success rate fluctuates significantly across batches, indicating variability in the model's performance on the train and test sets.

The lower plot focuses on the model's loss, which measures its error in predictions relative to the true values. The loss fluctuates considerably across the batches but shows a general downward trend, implying some level of learning progression as the training continues. Lower loss values typically indicate better model performance, and the decreasing pattern seen here suggests that the model is gradually optimizing its predictions over time.

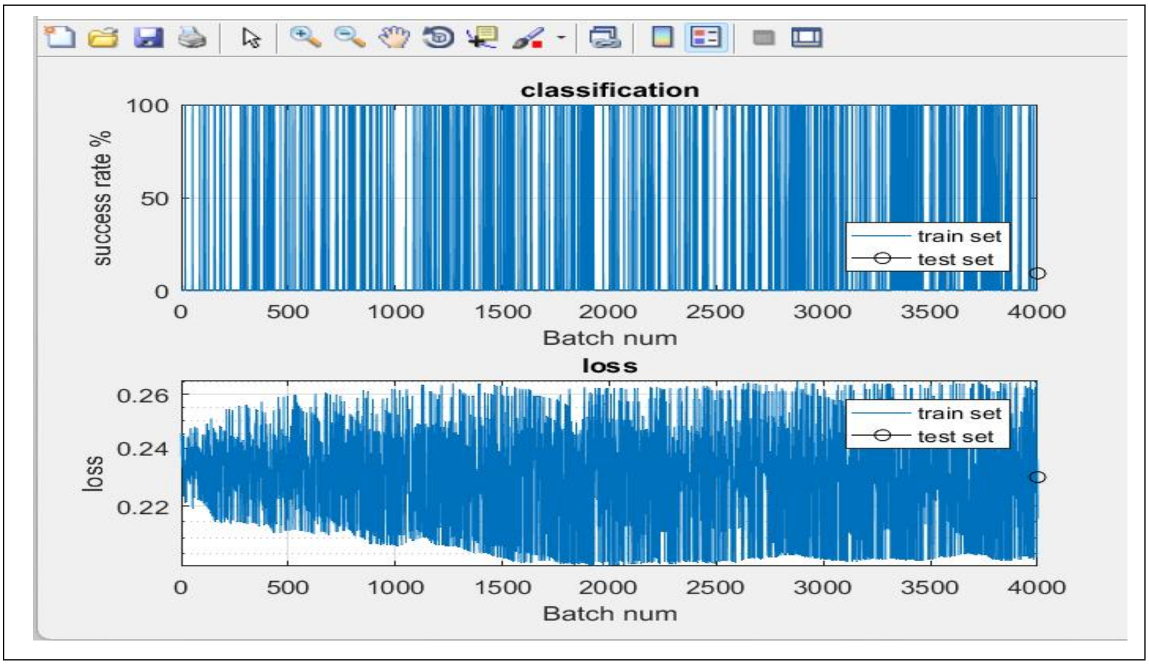

Fig.5.6.1 Success and Loss rate in Predictions

5.7 Histogram results for RGB Bands :

To further analyze the image enhancements, we generated separate histograms for the red, green, and blue (RGB) bands, along with a combined histogram. The x-axis represents the gray value, while the y-axis indicates the pixel count. These histograms provide a visual representation of the pixel intensity distribution across each color channel, helping us assess the contrast and brightness levels. By examining these outputs, we can better understand how different enhancements affect the visibility of features within the endoscopic images, ultimately supporting improved classification and diagnosis.

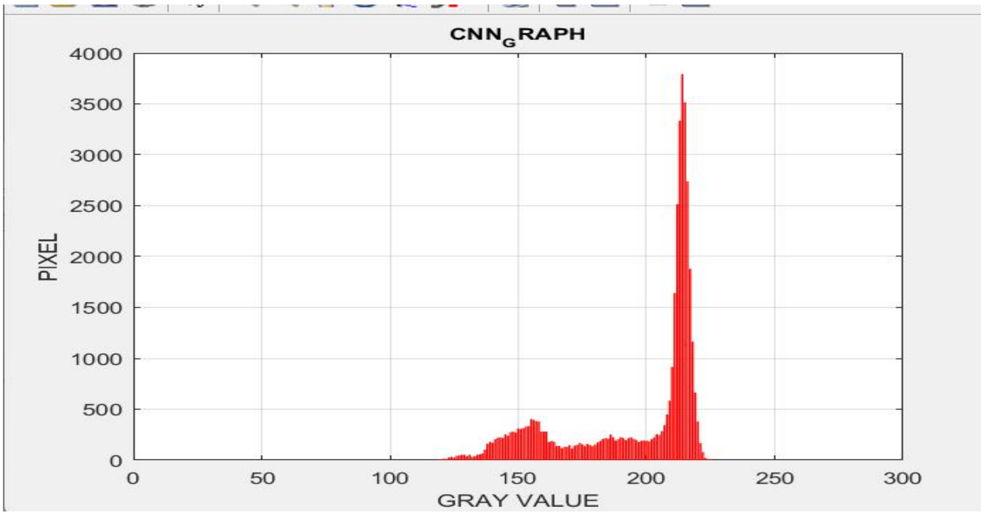

Fig.5.7.1 Red Band histogram

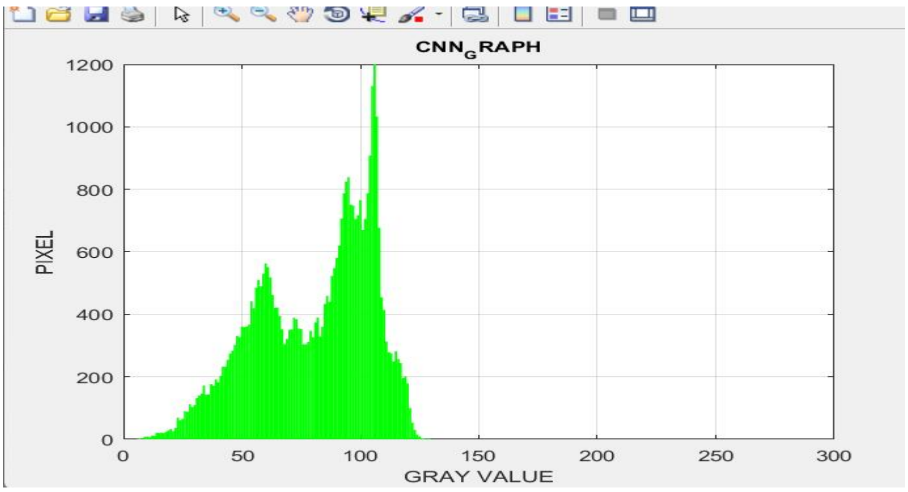

Fig.5.7.2 Green band Histogram

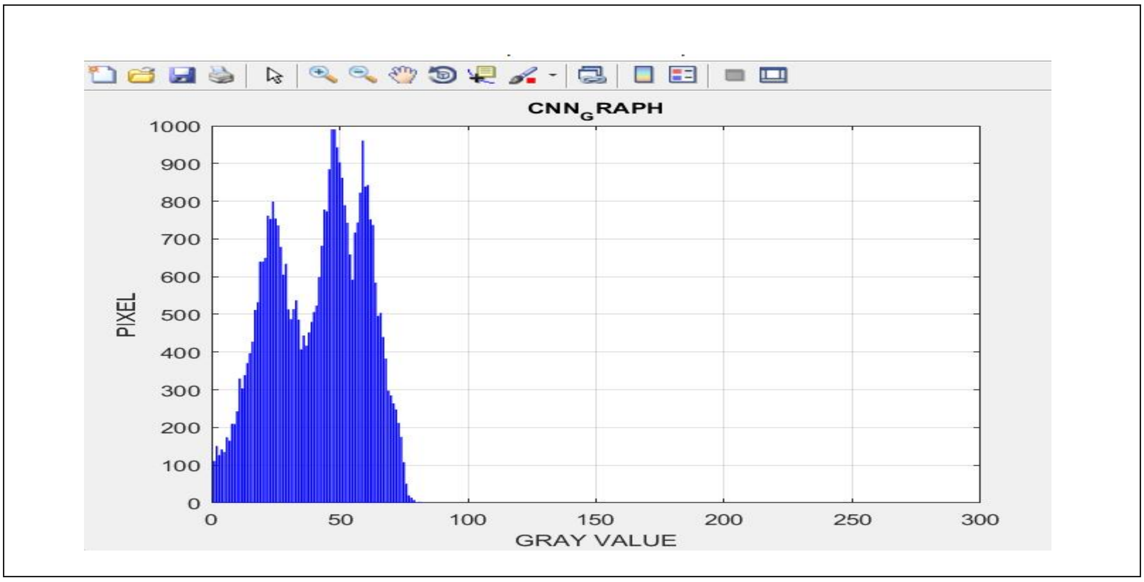

Fig.5.7.3 Blue band Histogram

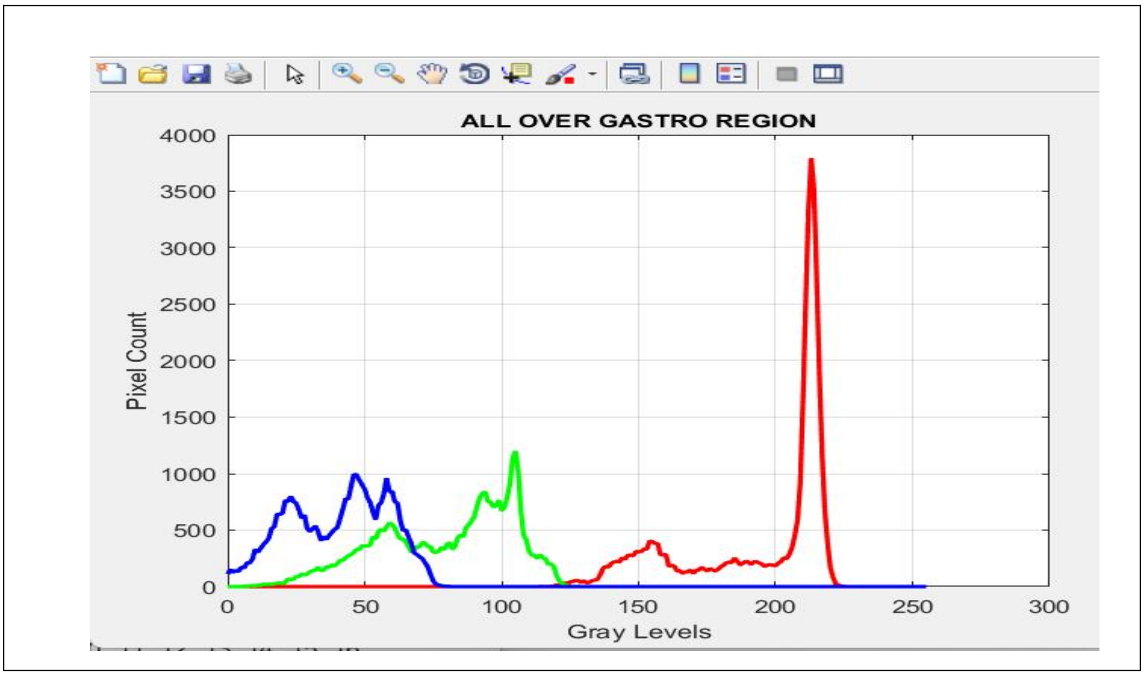

Fig.5.7.4 RGB Bands combined Histogram result

CHAPTER-6
CONCLUSION & FUTURE WORK

In this project, we successfully implemented a comprehensive image processing pipeline for the detection of gastric cancer, achieving a remarkable accuracy of 99.2% with our convolutional neural network (CNN) model after 800 iterations which is trained of 250 dataset images. The approach involved multiple preprocessing steps, including RGB to grayscale conversion, Gaussian filtering, edge detection, and segmentation, which collectively enhanced the quality of the input images and improved the model's performance. The use of various filtering techniques, such as median filtering and morphological operations, allowed us to minimize noise and highlight relevant features within the images. The results demonstrate the effectiveness of the proposed method in accurately identifying signs of gastric cancer, showcasing the potential of image processing and machine learning in the medical field.

For future work, we aim to expand the dataset to include a wider variety of gastric cancer cases and potentially incorporate other cancers for a more robust model. Additionally, exploring more advanced deep learning architectures, such as transfer learning with pre-trained models, could further enhance detection accuracy. We also plan to investigate the integration of real-time processing capabilities, enabling the system to analyze live images during medical examinations. Finally, addressing the interpretability of the model's predictions will be crucial in providing healthcare professionals with actionable insights, thus bridging the gap between AI and clinical practice.

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