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A Study on Preprocessing Techniques Used for Gastrointestinal Cancer Detection in Endoscopy Images

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***Abstract*---This study paper focuses on diagnosis of gastrointestinal (GI) cancer through the systematic preprocessing and analysis of endoscopic images. Usually the raw endoscopic data suffers from problems such as poor lighting condition, motion blur and artifacts like bubbles or reflections. These kinds of problems affect the clarity and quality of image. These limitations are overcome by applying preprocessing techniques to enhance diagnosis reliability by noise removal and quality enhancement. This outcome images are then evaluated through advanced computational methods. This study paper discusses various methods and preprocessing techniques to improve the quality of the image for further processing like feature extraction and segmentation. From this study median filtering provides strong results for noise reduction and improves quality of the image. This approach significantly strengthens diagnostic process and strengthens clinical decision making for gastrointestinal cancer detection.**

Keywords: GI Cancer, Machine Learning, Deep Learning, Preprocessing, endoscopy image.

I. INTRODUCTION

The digestive system refers to the gastrointestinal tract. Gastrointestinal tract is a long tube of organ through which the foods passes from mouth to anus. Gastrointestinal tract includes mouth, oesophagus, stomach, small intestine, large intestine and accessory organ such as salivary gland, liver, gallbladder and pancreas that produce digestive juices and enzymes for digestion. Below figure 1 shows the gastrointestinal tract. Endoscopy is a method to view the lining of the gastrointestinal tract directly to identify gastrointestinal cancer.

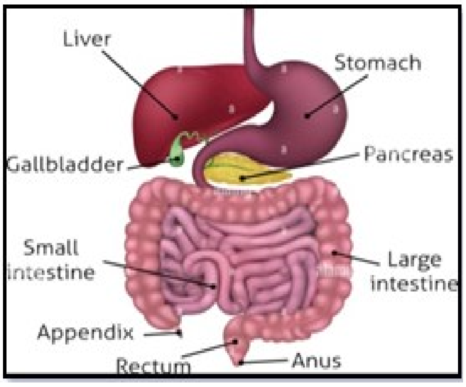

Figure 1. Gastrointestinal Tract.[1]

A traditional evaluation method within different imaging modalities often provides only partial information when medical imaging plays a vital role in the clinical assessment of cancer. Accurate identification and monitoring of cancers remain complex and challenging in oncology of research and clinical practice. [2].

Video endoscopy is a direct way of analysing and identifying gastrointestinal diseases or disorders like bleeding, ulcer, inflammation and polyps. When examining the patient through endoscopy method produces a huge number of images so, clinician needs substantial time for evaluation. This kind of manual evaluation is more complex therefore advanced computer assisted diagnostic system is introduced for analysing extensive image datasets rapidly and accurately [3]. As video endoscopy is a direct way of examining GI cancer it plays a vital role in early detection of polyps in GI tract. It significantly reduces mortality rates. It also analyses mucosal characteristics to evaluate the severity of ulcerative colitis by changes in colour and surface texture in of the GI lining. This detail visual observation enables physicians to distinguish between various disease stages [3].

A procedure of video endoscopy captures internal visuals using a small camera mounted on a flexible tube known as endoscope that is carefully inserted into the body through the mouth to analyse and observe internal organs and tissues. These visuals are displayed in real-time on a monitor, allowing healthcare professionals to scan organs such as the oesophagus, stomach, and intestines for diagnostic and therapeutic purposes. Figure 2 shows representation of video endoscopy

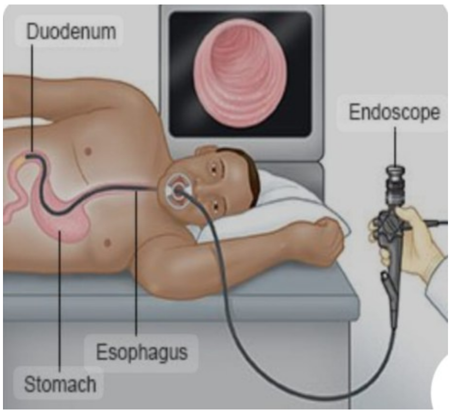

Figure 2. Representation of Video Endoscopy [4]

Various kinds of ML and AI algorithms are applied by researchers to analyse and classify endoscopic images for GI cancer. However, numerous troubles emerge during preprocessing due to the complex and variable nature of these medical images, which can affect tasks such as segmentation and feature extraction [5].

This study indicates that preprocessing has a direct impact on lesion boundary preservation during segmentation, edge enhancement techniques and contrast normalization improves boundary visibility enabling segmentation models to better identify lesion contours. Especially median filtering particularly suppress random noise while preserving structural edges which is critical for accurate boundary detection in GI lesions. Preprocessing must be carefully balance to enhance boundaries by without over smoothing diagnostically relevant details. When excessive smoothing may blur fine lesion margins particularly in early stage or flat lesions.

II. OVERVIEW OF PREPROCESSING TECHNIQUES FOR ENDOSCOPY IMAGES

Preprocessing is an acute step in preparing endoscopic images for further processing. Usually raw endoscopic image data often suffers from numerous challenges like variable illumination presence of mucus or bubbles, motion artifacts and differences in imaging equipment. Obviously these factors lead to reduce the reliability of automated detection algorithms. The main aim of preprocessing technique is to minimize or removal of noise, standardize quality of image, enhancing relevant features and removal of unwanted artifacts. Thereby generating a more uniform and reliable dataset.

Effective preprocessing of endoscopic images involves several crucial steps aimed at enhancing quality of image and making features more recognizable for subsequent analysis. Some of the widely used preprocessing techniques are shown in figure 3.

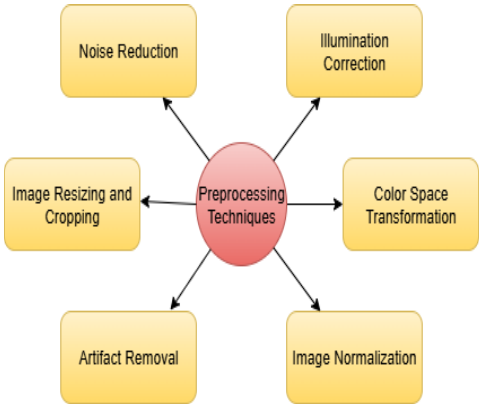

Figure 3. Preprocessing Techniques

By combining these preprocessing methods, the quality and useful information of endoscopic images are significantly enhanced, which directly contributes to the increased reliability and capability of automated systems for gastrointestinal cancer detection and assessment.

Due to reflection of light, variations in photographic angles and presents of mucous membranes around the internal organs in endoscopic images, noise and artifacts in gastrointestinal images often generated. These factors usually complicate feature extraction and can reduce performance metrics of CNN models. To address these challenges it is necessary to enhance the quality of image through preprocessing techniques has gained significant attention for researchers. In this study, GI images were preprocessed before fed into the CNN models to enhance their performance. General architecture for GI cancer detection is shown below n figure 4.

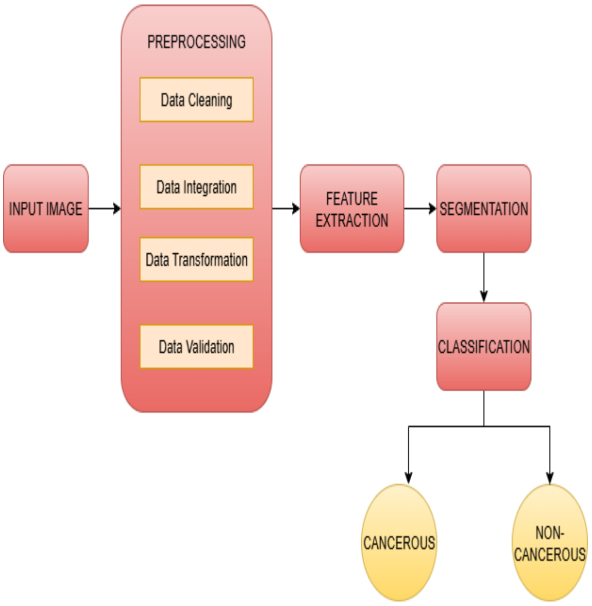

Figure 4. General Architecture Diagram For GI Cancer Detection

Multiple steps of preprocessing for gastrointestinal tract cancer endoscopy images improves image quality and produce feature easier for algorithms to analysis. These method help to bring standardize data, removes or reduce unnecessary data and highlight medically necessary details.

Preprocessing step such as resizing, edge enhancement and noise reduction like median and Gaussian filtering primarily enhance the description of anatomical structures and lesion boundaries for segmentation tasks. This paper highlights that encoder-decoder architecture such as U-Net and Mask R-CNN improves more accurate separation of lesion regions form the background by enhancing contrast and reduces artifacts. In contrast for classification tasks, preprocessing techniques mainly come up with robust feature representation and model generalization. Preprocessing techniques such as contrast enhancement (CLAHE, histogram equalization), normalization and artifacts removal which improvise the texture and color consistency and these features strengthens CNN based classifiers like GoogleNet, MobileNet and DenseNet121. It is discussed in the methods and discussion section as improved image quality directly leads to higher diagnostic confidence and improved detection rates in classification pipeline

Each image is resized and cropped to retain only the diagnostically important region, ensuring consistent dimensions and focus across the dataset [6][7]. Edge enhancement operations are performed for detecting boundaries and surface details with shaper description of anatomical structures [8]. Due to various lighting condition in endoscopy images noise may occur. To address these noise some filtering techniques like Gaussian and median filtering are applied. These filters can improvise the clarity of image and also easy to identify small lesion structures [8][9]. Another method like contrast enhancement such as histogram and CLAHE (Contrast Limited Adaptive Histogram Equalization) are used for balancing the intensity distribution for enhancing the visibility of internal structures [9]. The encoder and decoder networks like U-Net is performed for removing irrelevant information in background of image [10]. Finally, the filtering methods like mean and median are used to remove the random noise and artifacts presents in the endoscopy images [11]. The method such as Dn-CapsNets (Denoising capsule network) used for reducing the noise and improvise the relevant features [12].

III. OVERVIEW OF COMPUTATIONAL MEHODOLOGY

Machine learning and deep learning based preprocessing algorithms are specifically address the challenges of GI cancer in endoscopic images.

Traditional machine learning approaches have been applied to GI endoscopic images to extract features like colour, texture, and edges. This usually depends on iterative experimentation for diseases identification. In contrast deep learning models have established superior performance, often exceeding the diagnostic capabilities of expert clinicians when examining medical images. As a result Computer Aided Diagnostic systems using deep learning for endoscopic image interpretation offer the potential to achieve diagnostic performance metrics that surpasses that of highly trained medical specialists [3].

Generally a Convolutional Neural Network model depends on the quantity of training data with large datasets which leads to improve accuracy. Data Argument methods are frequently applied to improve CNN performance in classification task since, medical image datasets are often limited. These methods expand the dataset and correct class balance by creating additional samples through operations such as flipping, rotation, zooming, and shifting. In this study such augmentation techniques were utilized on the training images to strengthen model stability and overall accuracy [3]. The extracted attributes represent key visual characteristics of medical images to support more accurate analysis and classification [13].

Low resolution endoscopy images are improved by applying advanced super resolution algorithms that improve the visibility of fine details that are critical for early cancer detection [14].Machine learning techniques like feature based filtering removes noise and artifacts by filtering out irrelevant regions [15]. Deep learning based preprocessing methods like encoder and decoder

Networks are widely used to segment or detect regions of interest within endoscopy images. These networks isolate relevant anatomical structures and remove distracting background [16][17]. Self-supervised learning such as curriculum based self-supervised framework like modified SimSiam technique use large dataset for unlabelled GI images to learn robust feature representation [18].

IV. LITERATURE REVIEW FOR PREPROCESSING ALGORITHMS

AUTH OR	YEAR	METHODDS USED	LIMITATIONS
[18]	2024	This paper focuses on method such as texture and colour enhancement imaging (TXI) are used to detect the gastric adenocarcinoma.	By using this TXI method it is difficult to detect gastric adenocarcinoma of the fundic gland type (GA-FA).
[19]	2021	TXI often gives clearer lesion visuals compare to WLI, but it need additional large scale clinical studies are required to validate reliability in regular screening and diagnosis of early gastric cancer.	The impact of using TXI on improving detection rates in routine clinical practice is still unclear. Forward looking studies are needed to confirm its practical effectiveness and clinical value in real world applications.
[20]	2015	This approach utilizes an adaptive sigmoid function along with space variant colour reproduction to enhance low contrast grayscale and colour endoscopic images.	The paper does not specify particular limitations; however, it notes that the choice of theme image may lead to colour distortions.
[21]	2021	This paper uses methods like two colour enhancement modes, like C2 and C2 in blue laser imaging (BLI) technology to evaluate their efficiency in improving the visibility and colour contrast of early stage gastric cancer lesions.	Examining this method by non-experts did not show any significant advantage of C2 colour enhancement mode.
[22]	2020	Linked Colour Imaging (LCI) is an advanced endoscopic technique designed to enhance color contrast in gastrointestinal images. LCI utilizes both pre-processing and post-processing technologies to improve the visibility of mucosal details and lesions by amplifying color differences between abnormal areas and surrounding tissue	Limitations of this method include a limited sample size. Furthermore, the investigators are manually determined by the regions of interest (ROI).
[23]	2021	This paper uses modern endoscopic method like TXI (Texture and colour enhancement imaging) is designed to enhance the visualization and identification of gastric neoplasms and mucosal atrophy more effectively than WLI (White light imaging).	Limitation of this paper includes images are not created from the extract same WLI scam image. It focused only on gastric mucosal atrophy and neoplasms.
[24]	2016	The study of this paper uses colour based segmentation methods are commonly applied in medical image analysis to detect abnormal regions by examining differences in pixel colour and intensity.	By using this methods error arises when detection of distinct regions exhibit similar colour tones.
[25]	2015	This paper focuses on digital imaging technique such as flexible spectral imaging colour enhancement (FICE) method for detailed visualization ofmucosal and vascular structure during gastrointestinal endoscopy.	Present research does not support the use of FICE (Flexible Spectral Imaging Colour Enhancement) for routine colon cancer screening.
[26]	2023	This paper presents the canny edge detection method to segment medical images by locating and outlining their boundaries.	This paper needs more advanced modelling techniques and diverse dataset for improving the accuracy and classification.
[27]	2023	This paper focuses on preprocessing methods such as 3D median filtering for enhancing the quality of image and improvises the contrast os lesion in endoscopy images.	Identifying GI cancer in endoscopy images presents several difficulties including the similarity in colour tones between different tissue types.

			Including the presence of complex and crowded backgrounds that complete the process. Segmentation and detection of GI cancer is most challenging process both automated and manual diagnosis evaluation.
[28]	2022	The study of this paper uses preprocessing of hyper spectral data includes steps such as spatial and spectral smoothing to minimize noise and enhance signal clarity. Min-max scaling is used to normalize the data to maintain consistent range whereas SNV normalization compensates for intensity fluctuations and scattering effects. In addition to that median spatial smoothing is applied to further refine image quality by suppressing random noise within the spatial domain.	At present there is no preprocessing approach exists for hyper spectral data. The use of median filtering in preprocessing leads to inconsistent classification results indicates that its effectiveness may vary depending on the dataset characteristics and experimental conditions.
[29]	2021	This paper presents a combination of backprojection algorithm (BP) and support vector machine (SVM) methods has been utilized to standardize the diagnostic performance of MRI scans in detecting gastric cancer. These integrated methods are referred as BPS to enhance image interpretation by minimizing errors and improving the precision of malignant lesion detection.	The MRI image quality usually depends on several technical factors, including the strength of magnetic field , the design and performance of radiofrequency and gradient coils and key acquisition parameters such as repetition time and echo time.
[30]	2024	This paper uses advanced technology such as Computer Aided Detection (CADe) and Computer Aided Diagnosis (CADx) systems in GI endoscopy to support the identification and examination of abnormal growth.	Researchers uses Computer Aided Diagnosis (CADx) systems for detecting neoplasms in the upper GI tract remains relatively scare.
[31]	2022	In this paper Deep Learning has emerged as an effective approach in radiomics analysis that allows automatic extraction of intricate image features that represent detailed tissue properties in medical scans.	The field of radiomics and deep learning has rapidly grown issues such as the need for large datasets, complex algorithm, reproducibility, interpretability and validation still present significant hurdles.

V. METHODS AND DISCUSSIONS

To detect GI cancer through endoscopic images preprocessing is essential for enhancing the

precision and consistency of computer Aided Diagnostic system. According from current research images from Kvasir dataset often present challenges such as inconsistent resolution, inherit noise, presents of artifacts like mucus or bubbles and limited contrast between normal and affected tissue regions [32][33].

Notably, preprocessing not only improves the technical quality of images but directly impacts the robustness of deep learning models seen in approaches employing architectures such as U-Net, Mask R-CNN . GoogleNet, MobileNet, and DenseNet121. Enhanced images yield better feature representations, loading to higher detection rates and diagnostic confidence for GI cancer and related pathologies [10][11].

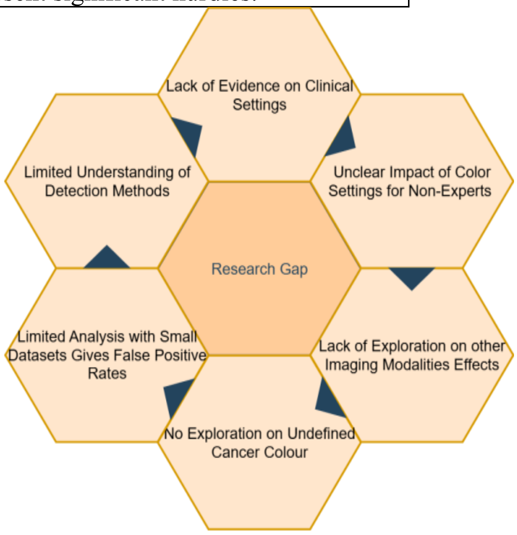

Figure 5. Research Gap GI Cancer Detection

Based on the literature review studied some of the research gaps are found for Gastrointestinal cancer detection that are shown in figure 5. Normally, median filtering improves noise suppression and feature clarity but its impact varies across CNN architectures like lightweight models such as MobileNet and GoogleNet benefits significantly form median filtering because noise reduction stabilizes feature extraction in shallow and depth wise convolution layers whereas deeper architectures like DenseNet121 median filtering enhances feature reuse by providing cleaner low level representations which increases gradient flow and convergence stability.

By analysing the existing preprocessing techniques in literature review table this comparison chart has been established used for gastrointestinal cancer using endoscopic images are shown in figure 6. From this chart overall diagnostics results for image based GI detection. Median filtering provides strong results for noise reduction and feature enhancement. Preprocessing enables DL models to popularize well to new cases, offering reliable support for clinical decision making.

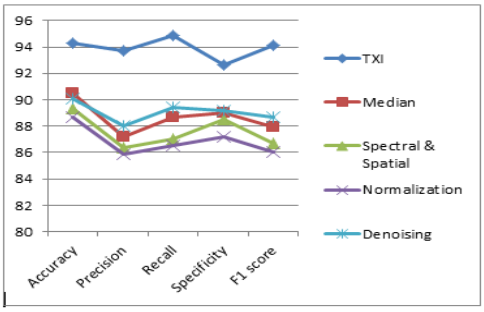

Figure 6. Comparison of Preprocessing Methodologies

VI. DATASET

Some of the available dataset for gastrointestinal cancer detection in online are given below

1. Kvasir Dataset: The Kvasir dataset contains endoscopic images of the gastrointestinal (GI) tract, encompassing both anatomical landmarks such as the Z-line, pylorus, and cecum, and pathological findings including polyps, esophagitis, and ulcerative colitis. All images are verified and annotated by expert endoscopists and are available in multiple resolutions ranging from 720×576 to 1920×1072 pixels. The dataset supports various research applications such as image classification, retrieval, and detection tasks in GI endoscopy and serves as a benchmark resource for developing and evaluating computer-aided detection systems in medical imaging.
2. TCGA-STAG (The cancer genome atlas stomach Adenocarcinoma): This dataset provides a comprehensive collection of clinical, histopathological, radiological, and genomic data related to stomach adenocarcinoma.
3. Gastrointestinal cancer MSI MSS prediction (Kaggle): This large-scale dataset includes over 190,000 histopathological images used for classifying gastrointestinal cancer samples based on (MSI) and (MSS).

VII. CONCLUSION

Based on literature review and dataset consideration the kvasir dataset is the best choice for achieving high accuracy as well as for doing segmentation and classification and easy way to detect GI cancer. The study of this paper acknowledges several limitations related to dataset bias and clinical generalizability. Although the kvasir dataset is well annotated and widely used it represents controlled accession settings and may not fully capture variability in real world clinical environments, such as differences in endoscopy equipment, operator expertise and patient community. Additionally the literature review highlights that many preprocessing techniques including TXI, LCI and median filtering lack large scale and multi-center clinical validation, limiting their immediate deployment in routine screening workflows. The absence of prospective clinical trials and real time validation remains a key limitation and future research direction.

Objective evaluation metrics used in this paper is to claim the superiority of median filtering objective image quality and task performance evaluation metrics such as PSNR (Peak Signal –to-Noise Ratio) and SSIM (Structural Similarity index measure) which are commonly adopted in gastrointestinal endoscopy image analysis. . Higher PSNR value indicates better noise removal with minimal loss of diagnostically relevant information. Higher SSIM scores are achieved by maintaining lesion texture and boundary integrity while reducing random noise, which is essential for accurate segmentation and feature extraction in GI endoscopy images. Compared to other linear filtering methods median filtering consistently yields higher PSNR/SSIM because it effectively removes impulse noise caused by mucus, bubbles and illumination artifacts without excessively smoothing the structural details of the image.

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