BioScientific Review (BSR)
Volume 5 Issue 2, 2023
ISSN$_{(P)}$: 2663-4198 ISSN$_{(E)}$: 2663-4201
Homepage: https://journals.umt.edu.pk/index.php/bsr

Article QR

Title:	**Emerging Trends and Advances in the Diagnosis of Gastrointestinal Diseases**
Author (s):	Muhammad Nouman Noor[1], Muhammad Nazir[1], Imran Ashraf [2]
Affiliation (s):	[1]Department of Computer Science, HITEC University Taxila, Pakistan [2]Department of Computer Engineering, HITEC University Taxila, Pakistan
DOI:	https://doi.org/10.32350/bsr.52.11
History:	Received: January 1, 2023, Revised: May 2, 2023, Accepted: May 8, 2023, Published: June 27, 2023
Citation:	Noor MN, Nazir M, Ashraf I. Emerging trends and advances in the diagnosis of gastrointestinal diseases. *BioSci Rev*. 2023;5(2):118–143. https://doi.org/10.32350/bsr.52.11
Copyright:	© The Authors
Licensing:	This article is open access and is distributed under the terms of Creative Commons Attribution 4.0 International License
Conflict of Interest:	Author(s) declared no conflict of interest

A publication of
The Department of Life Sciences, School of Science
University of Management and Technology, Lahore, Pakistan

Emerging Trends and Advances in the Diagnosis of Gastrointestinal Diseases

Muhammad Nouman Noor [1*], Muhammad Nazir [1], and Imran Ashraf [2]

[1]Department of Computer Science, HITEC University, Taxila, Pakistan
[2]Department of Computer Engineering, HITEC University, Taxila, Pakistan

ABSTRACT

Recently, Artificial Intelligence (AI)-based techniques, namely machine learning (ML) and deep learning (DL) have gained exceptional devotion in conducting the analysis of medical images because of their capacity to provide outstanding results that can compete with specialists. Despite the rise of artificial intelligence-based research on peptic ulcer diseases, limited reviews are available concerning this area. For this purpose, the researcher reviewed artificial intelligence techniques used for detecting and classifying gastrointestinal diseases in wireless capsule endoscopy images. Furthermore, this study investigates the tremendous potential for peptic ulcer disease that has been cited in the prior literature. The findings demonstrated the value of WCE picture analysis using machine learning and deep learning techniques. Additionally, further, limitations were found in the availability of datasets and assessment measures, which have an impact on the reproducibility of experiments.

Keywords: deep learning, gastrointestinal, machine learning, medical imaging, peptic ulcer

1. INTRODUCTION

Gastrointestinal Tract (GI Tract) is a chain of void organs, linked in a protracted and bendy tube starting from the mouth to the anus, which is used for the digestion of food in the human body. The mouth, esophagus, stomach, small intestine, large intestine, and anus are among the GI tract's void organs. Esophagus is a hollow tube starting from the mouth to the stomach, and then the small intestine starts, which has three organs called as duodenum, jejunum, and ileum. The large intestine comprises of appendix, cecum, colon, and rectum. Some common problems that occur in the digestive system are colitis, diverticulitis, gastroenteritis, heartburn, and ulcers.

Infections called peptic ulcers can develop in the lower esophagus, small intestine, or stomach lining. They often appear as a result of corrosion brought on by gastric acids, as well as, inflammation that can be caused by the H. pylori bacterium. Over the past two centuries, peptic ulcers have indicated a serious risk to people all over the world, with a high morbidity and mortality rate [1]. There are three different types of peptic ulcers: duodenal [2], esophageal [3], and gastric [4]. The stomach area is where a gastric ulcer, which is also known as a stomach ulcer forms, whereas the esophagus area is where an esophageal ulcer grows and the duodenum area is where a duodenal ulcer develops.

Peptic ulcers can lead to scar tissue formation, haemorrhage, and perforation [5]. Bleeding can result in significant blood

* Corresponding Author: nouman.noor@hitecuni.edu.pk

loss, necessitating the hospitalization of patient. Dizziness, lightheadedness, and black stools are signs of a bleeding ulcer. A hole forms inside the stomach or small intestine lining after a perforation, which results in an infarction. A perforated ulcer can cause sudden and acute intestinal pain. After an injury, thick tissue called scar tissue may develops. A person's ability to eat is hampered by this tissue because food cannot easily travel through the digestive tract. Therefore, vomiting and loss of weight becomes two of the main signs of scar tissue.

Breakdown in the lining of the small intestine, esophagus, and stomach that can be caused in a variety of reasons. These include the bacteria Helicobacter pylori (H. pylori) [6], which causes stomach ulcers and infections. Moreover, the routine use of aspirin, ibuprofen, and other anti-inflammatory drugs (people over 60 and women are at a higher risk), smoking, excessive alcohol consumption, and radiation therapy can cause gastrointestinal cancer. Ulcers and Cancer can be differentiated by their symptoms. Normally, Ulcer has milder symptoms than Cancer.

The most common sign of a peptic ulcer is the immense burning and pain in the abdominal area that extends from the navel to the chest, which can be mild to severe in intensity. There are times when the agony would keep you up at night. Early on, small peptic ulcers may not show any symptoms. Other symptoms of a peptic ulcer, include changes in appetite, nausea, bloody or dark faeces, unexplained weight loss, indigestion, vomiting, and severe chest pain.

Traditionally, doctors spend 2-3 hours to analyze images of endoscopy for diagnosis of gastrointestinal diseases. It consumes much time and is prone to error depending on the expertise of the physician. Furthermore, the highest achieved accuracy in this method is 85%, respectively. Therefore, many researchers used different machine and deep learning techniques for the detection of peptic ulcers to help save doctors' time with greater accuracy. The major steps followed by computer vision researchers are shown in Figure 1.

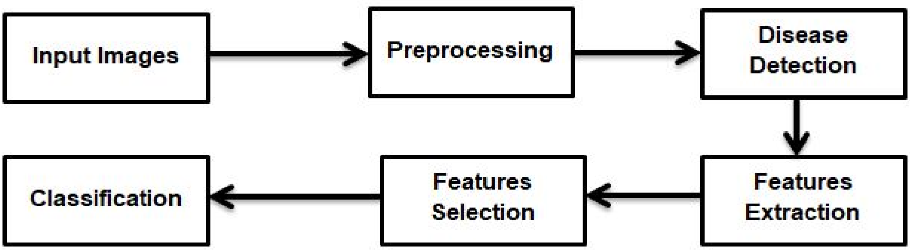

Figure 1. General Steps for Classification of Gastrointestinal Diseases

The main highlights of this paper are given below:

- This article discusses the stats about peptic ulcer in the world, which significantly highlights the alarming situation this disease is creating.
- This article discusses and summarizes different available endoscopic datasets.
- This article also discusses and summarizes machine learning and deep learning techniques applied for

the recognition of various gastrointestinal diseases.

1.1. Stats about Peptic Ulcer

It is a serious requirement to model peptic ulcer detection as complications related to peptic ulcer disease continue to have significant health problems with high demand in health care systems despite having a complete treatment of H. Pylori. Further case studies, especially in developing countries, should be conducted to define the global epidemic and determine what factors are contributing to the crisis. As per the study published in 2022, estimated cases of new peptic ulcer or cancer have caused a large number of deaths by gender, in the US, which are shown in Figure 2.

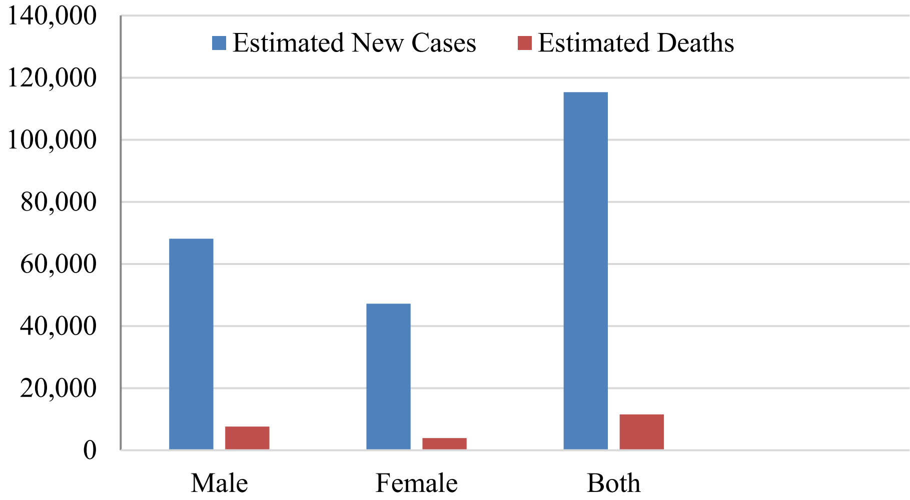

Figure 2. Estimated Death Rate and New cases in 2022

The bacteria H. Pylori that causes peptic ulcer is increasing the world population as per the study published in the year 2020, more than 50% of the world's population is colonized by this bacteria. However, in the developed countries, a 37% increase in peptic ulcers was observed in adults ranging from 18-39 years [2]. Moreover, worldwide figures for patients diagnosed with peptic ulcer are shown in Table 1.

To study the spread of H. Pylori infection in people from rural areas of Pakistan, researchers have investigated the invulnerable response in gastrointestinal patients by amplifying a small layer of immunoassay from the H. Pylori site. It was found that the relation between the rates of spread of infection H.Pylori with the persons' age was significantly higher between the age group of 15-25 years, which was 73%, respectively and 25-35 years was 67% as compared to the middle age persons of 45-55 years that was 58%, respectively, whereas 5565 years was 53%, respectively. Hence it is shown that middle-age persons have a lower risk of H.Pylori infection. Male patients of age between 15-25 years have been shown to have a higher risk of infection at 36%, while older patients of age between 55-65 years have been shown to have a low percentage of H. pylori-infected patients at 12%, respectively. In contrast, a higher risk of infection in women was found between the ages of 65-75 as 50%. Female patients between 15-65 years were shown to have a moderate risk of infection at 36-43%.

For comparing the statistics of deaths from peptic ulcer disease for the year of 2021, worldwide stats of various available countries are shown in Figure 3. The highest ratio of death can be seen in Kazakhstan with 736 persons and the lowest is in Qatar with only 1 person dying.

1.2. Tests Available for Endoscopy

Different sorts of tests are accessible to diagnose a gastrointestinal ulcer. They are termed as upper-endoscopy, upper-gastrointestinal (GI) series, and Wireless Capsule Endoscopy. There are many computerized techniques discovered by the researchers, which are used for the detection of peptic ulcer, one of them is wireless capsule endoscopy [8].

Table 1. World Figures of Peptic Ulcer Patients [2]

Country	Data Source	Peptic Ulcer		
		General Incidence (person years)	Bleeding Incidence (person years)	Perforated Incidence (person years)
Canada	Quan 2014		37.85	
USA	Feinstein 2010	62.03		
	Laine 2012		40.16	
Malaysia	Lee 2014		1.80	
South Korea	Bae 2012 a,b		22.10	4.40
Denmark	Lassen 2006		57.78	8.30
Finland	Malmi 2014	93.33	46.33	
Germany	Ohmann 2004		48.70	
Greece	Theocharis 2008		72.50	
Italy	Loperfido 2009		47.60	
Netherland	Ramsoekh 2005		21.50	
Norway	Bakkevold 2013		45.00	
	Thorsen 2013			6.50
Spain	Lanas 2011		31.32	3.88
	Perez-Aisa 2005	141.90	79.70	8.00
Sweden	Lu 2012		15.71	
	Ahsberg 2011	57.75	38.15	10.66
UK	Taha 2008			12.17

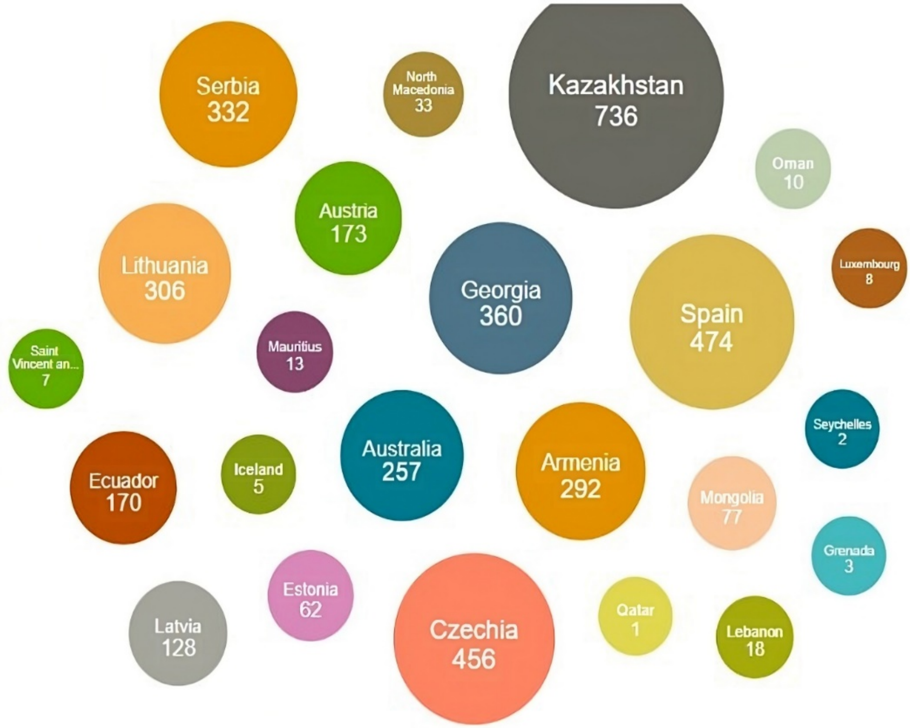

Figure 3. Estimated Death Rate of Peptic Ulcer [7]

In the Upper endoscopy procedure, the doctors insert a long tube, which usually has a camera at the end of it, from the throat into the small intestine and stomach of the patient to examine the region for ulcers. The doctor can also remove tissue samples with the help of this gadget for examination. In rare cases, an upper endoscopy surgery is not required. However, patients who have a higher risk of gastrointestinal cancer are advised to follow this procedure. This covers people having symptoms over the age of 45, as well as, those who exhibit anaemia, gastrointestinal bleeding, weight loss, and swallowing difficulties. The doctor might suggest an upper GI test in place of a swallowing test if the patient does not have any difficulty swallowing and has a low risk of gastrointestinal cancer.

The patient takes barium, a thick liquid, for an upper GI test. A technician would then take an X-ray of the patient's stomach, esophagus, and small intestine. The fluids would allow the doctor to see the ulcer and treat it.

A colonoscopy is an operation used to inspect the colon or digestive organ to analyze gastrointestinal illnesses like incendiary entrail infection and colon malignant growth. Additionally, it is useful in treating and forestalling colon disease. The technique includes embedding a long, adaptable cylinder called a colonoscope through the rectum and into the colon, which sends live video of the colon to a screen. During the assessment, the medical services supplier can, likewise, eliminate any unusual developments, called polyps, from the colon, which can be sent for additional testing to decide whether they are dangerous or not. Routine colonoscopies are suggested for moderately aged and more established grown-ups to evaluate for colon malignant growth, as early recognition can work on the possibilities of effective treatment. The strategy is by and large viewed as protected, however, like any operation; it conveys a few dangers, like draining or hole of the colon. In any case, the advantages of early malignant growth discovery far offset the dangers related to the method.

Wireless Capsule Endoscopy (WCE) is a camera-containing capsule. The doctor gives a capsule to a patient and as normal medicine is taken; the capsule is swallowed by a patient. This capsule, while moving from mouth to stomach captures almost 60,000 images, which are transmitted in real time. The physician should check the complete images for an average of 2-3 hours before making any conclusion during a single test [9], which is very time-consuming as well as hectic. An image elucidating the WCE capsule is shown in Figure 4 that is given below:

Figure 4. WCE Capsule [10]

1.3. Need for Computer-Aided Systems in Diagnostic of Endoscopy

The endoscopy has a few advantages, despite the fact that it shows up with specific compromises, for example, an immense number of casings are created (video accounts) from the screening technique of GI lot. Assuming that in this research only the endoscopy of an individual is considered, it can require as long as 45 minutes to 8 hours to finish the screening technique and around in excess of 10 thousand endoscopy outlines are created, contingent upon the objective of GI region. The time taken by the endoscopic interaction relies upon the objective GI region and abilities of the gastroenterologist. A highlighted note has been indicated here that defines that all endoscopic edges are not helpful to the gastroenterologist in light of the fact that the majority of the casings are in excess and just a few images might have a few unusual tissues [11]. Hence, the rest of the images that do not contain any anomaly can be disposed of by noticing each casing [12].

Furthermore, it is a troublesome and extended process for specialists to independently notice each edge. Then, the strange edges cannot be entirely obvious to the clinical specialists. Subsequently, clinical professionals request such frameworks that can consequently find possible malignancies by investigating the endoscopic edges.

Computer-supported diagnosing frameworks are machine-vision-based frameworks utilized for aiding specialists in the examination of endoscopic imaging information. In a commonplace particularly framework, a choice is made on each casing in light of different qualities (highlights), which were separated from the edges. Nonetheless, a few frameworks are just a sub-part of an entire computer-supported diagnosis framework, the result of these frameworks is a picture rather than a classifying decision [13, 14]. Just with the end goal of irregularity identification, a computer-supported diagnostic framework accepts an image as info and returns a choice in view of its qualities [15, 16], whether the image has a typical mucosal construction or some distortion, such as ulcer and polyps.

1.4. Datasets for Gastrointestinal Diseases

Many different datasets are developed for gastrointestinal disease segmentation and classification [17] like CVC-356, CVC-ClinicDB, KID, WEO Clinical Endoscopy Atlas, and many more [18]. Each dataset has different classes and is developed for specific diseases. CVC-356 [19] contains 356 images and only Polyps label, similarly, other datasets that have only polyp labels are CVC-ClinicDB, CVC-VideoClinicDB, CVC-ColonDB, ASU-Mayo polyp database, ETIS-Larib Polyp DB, and Kvasir-SEG. CVC-ClinicDB [20] has 612 images, CVC-VideoClinicDB [19] has 11954 images, CVCColonDB [21] has 380 images, the ASU-Mayo polyp [22] database has 18,781 images, and similarly, Kvasir-SEG [23] has 1000 images.

There are other datasets that just contain GI Lesions labels, such as Gastrolab, the WEO Clinical Endoscopy Atlas, the Atlas of Gastrointestinal Endoscope, the El Salvador Atlas of Gastrointestinal Video Endoscopy, and the GI Lesions in the dataset from Regular Colonoscopy. The Weo Clinical Endoscopy Atlas has only 152 samples, the Atlas of Gastrointestinal Endoscope contains 1295 sample images, the El Salvador Atlas of Gastrointestinal Video

Endoscopy contains 5071 videos, and the GI Lesions in Regular Colonoscopy dataset, which contains just 76 samples. Particularly, 100 sample images and a few sample videos are included in Gastrolab [24].

The Kvasir dataset contains 8000 images and 8 classes, which are Esophagitis, dyed resection margins, Z-line, polyps, ulcerative colitis, pylorus, cecum, and dyed polyp. GIANA 2017 dataset [25] contains 38 videos and 3462 images and has two classes of Angiodysplasia and Polyps, however, another version of the GIANA dataset was launched in 2018 called GIANA 2018 [26, 27] contains 38 videos and 8262 images with two major classes' Small bowel lesions and Polyps. One more dataset named Endoscopy Artifact Detection 2019 [28] was prepared in 2019, it contains 5,138 images and has only Endoscopic Artifacts labels. HyperKvasir is the name of a large dataset. A complete multi-class image and video dataset for gastrointestinal endoscopy includes diseased results, anatomical landmarks, and normal findings that were published in 2020. It contains 110,079 sample images and 374 sample videos [18].

Reportedly, among the availability of this dataset, only a few datasets were available publically for academicians like CVC-ClinicDB, Endoscopy Artifact Detection 2019, KID, GASTROLAB, Kvasir, and Kvasir-SEG. Whereas some datasets can be available by requesting the author or institute that developed the datasets, a few of them are GIANA 2017, GIANA 2018, WEO Clinical Endoscopy Atlas, and GI Lesions in Regular Colonoscopy Data Set. Among the aforementioned datasets, many are not available now like CVC-356, CVC-VideoClinicDB, CVC-ColonDB, ASU-Mayo polyp database, KID, and Atlas of Gastrointestinal Endoscope. Some of the datasets like GASTROLAB, WEO Clinical Endoscopy Atlas, and El salvador atlas of gastrointestinal video endoscopy are not usable for machine learning as they contain low quality images of different findings in GI tract, however, they can be used for educational purposes. The summary of above-discussed datasets is shown in Table 2.

Table 2. Summary of Gastrointestinal Findings Datasets

Dataset	Different Findings	Dataset Size	Accessibility	Comments
CVC-356	Polyps	356 images	Inaccessible	
CVC-ColonDB	Polyps	380 images	Inaccessible	
CVC-ClinicDB	Polyps	612 images	Openly Available	
CVC-VideoClinicDB	Polyps	11954 images	Inaccessible	
KID	Angiectasia, inflammations, polyps and bleeding	2371 images and 47 videos	Inaccessible	
GIANA-2017	Angiodysplasia and Polyps	3462 images and 38 videos	Available on Request	

Dataset	Different Findings	Dataset Size	Accessibility	Comments
GIANA-2018	Small bowel diseases and Polyps	8262 images and 38 videos	Available on Request	
GI Lesions in Regular Colonoscopy Data Set	GI Diseases	76 images	Available on Request	
WEO Clinical Endoscopy Atlas	GI lesions	152 images	Inaccessible	Not usable for machine learning
Kvasir V1/V2	Z-line, pylorus, cecum, ulcerative colitis, polyps, esophagitis, dyed polyps, and dyed resection margins	4000/8000 images	Openly Available	
Kvasir-SEG	Polyps	1000 images	Openly Available	
Endoscopy Artifact Detection 2019	Endoscopic Antiquities	5138 images	Openly Available	
ETIS-Larib Polyp DB	Polyps	196 images	Openly Available	
Atlas of gastrointestinal video endoscopy	GI Diseases	5071 video clips	Openly Available	Not usable for machine learning
Mayo polyp database	Polyps	18,781 images	Available on Request	
GASTROLAB	GI Diseases	100s of images and some videos	Openly Available	Not usable for machine learning
Hyper-Kvasir	Anatomical Landmarks, Pathological Findings, Therapeutic Interventions, Quality of Musocal Views	110,079 images and 374 videos	Openly Available	

The main findings in gastrointestinal diseases datasets are anatomical landmarks, pathological findings, therapeutic interventions, and quality of musocal views.

1.5. Anatomical Landmarks

Anatomical landmarks, which are used for the navigation are plainly visible during the endoscopy and are a distinguishable feature of the GI tract (Gastrointestinal tract). It serves as a place description and a point of reference for specific findings. Both the upper GI tract and the lower GI tract have anatomical markers. The lower GI tract is made up of the rectum, colon, and ileum, whereas the upper GI tract is made up of the esophagus, stomach, and duodenum. Z-line, Pylorus, ileocecal valve, and cecum are some examples of anatomical landmarks. The Z-line denotes the boundary between the esophagus and the stomach. The pylorus is a tiny aperture that separates the stomach from the duodenum, which is the beginning of the small intestine. The ileocecal valve is a mark of transition from small to large bowel. This transition prevents the reflux of stool back to the small bowel. The cecum is a centralized part of a large bowel. During a colonoscopy, when you reach the cecum, it is an indication that the colonoscopy is completed [29].

1.6. Pathological Findings

A pathological finding is an abnormality in the GI tract, due to some ailment, which can be viewed as visible damage in normal mucosa. Some of the pathological findings are Esophagitis, Polyps and Ulcerative Colitis. Esophagitis is an irritation in the esophagus and can be detected as a break in the area in relation to the z-line. Polyps are sores in the bowel. It can be observed as an outgrowing mucosal. Ulcerative colitis is an infection in the large bowel, due to which mucosa swells and appears as reddish.

1.7. Therapeutic Interventions

These are the findings required to treat the lesions which are detected in pathological findings. Examples of therapeutic interventions are Dyed Lifted Polyps and Dyed Resection Margins.

1.8. Quality of Mucosal Views

Visualization of complete mucosa is very important in order to identify all the pathological findings. In the colon, the Boston Bowel Preparation Scale (BBPS) exists which is a categorization of mucosal view in terms of quality.

1.8.1. Problems in Gastrointestinal Datasets. There are many problems that arise in datasets for developing machine learning or deep learning models. One of the major problems is the number of images for each class/label is not balanced as one ailment occurs more than other, which is a worldwide challenge in medical field [23]. Moreover, resolution of images varies from 720x576 up-1920x1072 pixels [23]. Furthermore, many other unwanted artifacts in endoscopic images are present like lighting issue in images, black edges, and corners around the images and textual information, which is written in the images and is helpful for the doctors' investigation [18, 23].

1.8.2. Machine Learning Classifiers and Deep Layers. In machine learning, features are hand crafted and multiple classifiers are applied on these features for classification tasks. In deep learning, human intervention is minimal and features are extracted by the model itself, and a classification task is performed on these extracted features. The various available machine learning classifiers [30] are as follows:

1.8.2.1. Decision Trees. Decision Trees are one of the most well-known and generally utilized ML classifiers. They work by breaking down a dataset into increasingly small subsets, at the same time, a comparable decision tree is progressively evolving. The end product is a tree with choice hubs and leaf hubs. The choice hubs, which address the split focus for the information, are produced by choosing the best highlights to part the dataset on at each step.

1.8.2.2. Random Forests. Random Forests is a group learning procedure that consolidates different choice trees to work on the exactness of the model. In this procedure, numerous choice trees are prepared on various subsets of the preparation information and the last result is acquired by taking the normal results of the multitude of individual trees.

1.8.2.3. Support Vector Machines (SVMs). SVMs are strong and well-known ML classifiers that are utilized for both relapse and characterization undertakings. They work by finding the hyperplane that best isolates the information into various classes. Especially SVMs are valuable, when working with datasets that have an enormous number of elements.

1.8.2.4. Naive Bayes. Guileless Bayes is a probabilistic classifier in view of Bayes' hypothesis, which expresses that the likelihood of speculation (for this situation, a specific class) is straightforwardly relative to the likelihood of the proof (for this situation, the noticed information). Innocent Bayes is frequently utilized for message characterization, spam separating, and feeling investigation.

1.8.2.5. K-Nearest Neighbors (KNN). KNN is a basic and natural ML classifier that works by finding the k nearest preparing models in the element space and doling out the class mark of most of those k guides to the test model. KNN is frequently utilized for picture acknowledgement, proposal frameworks, and inconsistency recognition.

1.8.2.6. Artificial Neural Networks (ANNs). ANNs are ML classifiers enlivened by the design and capability of the human mind. They are made out of interconnected hubs (neurons) that can figure out how to perceive designs in the information. ANNs are, especially valuable for complex order issues, like picture and discourse acknowledgment.

1.8.2.7. Gradient Boosting. Gradient Boosting is another group learning strategy that joins various frail students, such as decision trees that help to make areas of strength. In this strategy, each frail student is prepared to work on past the mistakes made by earlier students. Slope Helping is in many cases utilized in the field of information science for prescient displaying, positioning calculations, and abnormality identification.

The deep learning model has several deep layers that are stacked above each other. The input dataset pass through these layers for extraction of significant features, the working of these layers is as follows:

1.8.2.8. Convolutional Layer. The convolutional layer is the center structure block of a convolutional neural network (CNN). This layer conducts include extraction by applying a slew of learnable channels to the information picture or component map. The channels slide over the info and process speck items between their loads and the information values. The subsequent result is a component map that features the presence of the learned examples in the information.

1.8.2.9. Pooling Layer. The pooling layer is ordinarily utilized after the convolutional layer to lessen the spatial elements of the component map, while protecting the significant highlights. This layer applies a down sampling procedure on the component map by taking a sliding window over it and figuring a synopsis measurement, like the greatest or normal, for every window. The subsequent result has a more modest spatial size, which diminishes the number of boundaries and calculations in the organization.

1.8.2.10. Recurrent Layer. Recurrent neural networks (RNNs) utilize intermittent layers to handle successive information, like time-series or normal language. These layers store a secret express that is refreshed at each time step and contributes back to the next time step. This permits the organization to catch transient conditions and long-haul conditions in the information. Normal variations of repetitive layers incorporate the vanilla RNN, the long-short-term-memory layer, and the gated-recurrent-unit layer.

1.8.2.11. Dense Layer. The dense layer, otherwise called the completely associated layer, is the most fundamental kind of layer in a neural network. This layer is associated with each neuron in the past layer in which every ongoing layer is associated with the ongoing layer that has a learnable weight. The thick layer plays out a straight change of the information followed by a nonlinear enactment capability. This layer is ordinarily utilized as the result layer of a brain organization to deliver the last forecast.

1.8.2.12. Dropout Layer. The dropout layer is a regularization strategy that haphazardly exits a negligible portion of the information units during their preparation. This layer forestalls overfitting by constraining the organization from learning excess portrayals and making it more strong to a commotion in the information. The dropout layer can be applied after a layer, for example, a convolutional layer, pooling layer, or thick layer.

1.8.2.13. Batch Normalization Layer. The batch normalization layer is a method used to standardize the contribution to a layer to have zero mean and unit fluctuation. This layer speeds up the preparation and works on the speculation of the organization by decreasing the inner covariate shift. The clump standardization layer is regularly applied after the enactment capability in a brain organization.

1.9. Machine Learning Techniques for Gastrointestinal Diseases

For predicting the various forms of gastrointestinal diseases, many researchers have utilized a wide variety of conventional machine-learning algorithms. A gastric ulcer recognition-based machine learning model was created by Grace Lai, Hung Wong, and colleagues [31] using data from a historic cohort of 22, 854 patients (training cohort) who were diagnosed with the condition in 2007–2016. According to him, the maximum accuracy obtained using logistic regression and ridge-regression was 82.6% and 83.3%, respectively. A review evaluation-based framework for gastrointestinal disease identification was suggested by the authors [32], and its effectiveness and strength were tested using a significant WCE images dataset made up of 1,504 independent endoscopic videos. Consequently, his method/performance framework resulted in the best ROC-AUC, which was 0.9235, respectively. Moreover, in their study [33], the authors proposed a fully automated approach to diagnose a stomach illness. Reportedly, to identify stomach infections, a wide variety of features, including handcrafted features and fused features were applied. The primary issue with GI tract infections was that the pattern of the affected area shared a lot of similarities with each other. Khan then unveiled a contemporary CAD, which included handcrafted, fusion, and deep CNN elements. Datasets from Kvasir, CVC-ClinicDB, Private, and ETIS-LaribPolypDB were used in this study. Using this dataset, they were able to reach an accuracy of 96.5%, respectively.

The effectiveness of several visual descriptors for ulcer diagnosis utilizing WCE (Wireless Capsule Endoscopy) frames were compared to the prior research [34]. The goal of this research was to identify visual description more accurately detect gastrointestinal ulcers that portrays WCE frames. SVM classifiers and various visual descriptors were combined during the experiments. The authors used the LBP descriptor in conjunction with the SVM classifier to reach a maximum accuracy of 98.85%, respectively. To detect bleeding and ulcers, Jinn-Yi Yeh et al. [9] used a method of color characteristics and the WCE pictures dataset. They utilized texture information in addition to compiling all of the image attributes into a single matrix. This feature matrix was fed into a variety of classifiers, including decision trees, neural networks, and support vector machines. A variety of performance metrics were used to evaluate the system, and the accuracy ranged from 92.86%-93.64%, respectively. They work to fix the issues with poor contrast photos and variations in lesion shape. Moreover, the authors [35] proposed a brand-new automated method for classifying WCE photos in an effort to address these issues. They put into practice a cutting-edge technique for the automated detection and classification of intestinal illness. The suggested automated method was used by the authors, who attained a maximum accuracy of 98.3%, respectively. A computer-aided system for precise diagnosis of stomach illnesses from WCE images was projected by Rashid et al. [36]. The system as it is now given includes four fundamental processes, the first is HSI colour transformation before active contour segmentation is applied. The YIQ colour space is then used to build the saliency-based technique. Image fusion is then carried out. The retrieved features were then fused using SVD, LBP, and GLCM as the final step. In the end, neural networks are used to classify the gathered data. The dataset contains 9 thousand samples of stomach lesions like ulcers, bleeding, and healthy.

Amit et al. [37] presented a computerized aided technique to discover multiple gastrointestinal diseases GI from WCE videos. In this paper, the least-square saliency transformation (LSST) technique was followed by the probabilistic model-fitting approach. LSST was used to detect the set of best initial coefficient vectors, later utilized to catch the outstanding pixel of interest (POI) from a dataset of WCE images that had no pixelannotation. Different histogram-oriented gradients (HOG) features were combined, which were extracted from LBP (Local Binary Patterns), and were then passed to extreme machines for learning and detecting stomach diseases [38]. In [39] utilized a Neural Network to meld includes and got 95.5% accuracy and 92.8% F1 score, which worked on the presentation of diagnosing thyroid knobs. In another research [40], the author combined carefully assembled multiple handcrafted features like LBP, DWT, and GLCM. This framework accomplished promising outcomes for diagnosing endoscopy images of the gastroenterology informational collection. The method achieved 98.60% accuracy, respectively. A summary of machine learning based techniques were used for the prediction of peptic ulcer that is shown in Table 3.

Table 3. Summary of Machine Learning Techniques for Peptic Ulcer Prediction

Year	Technique	Dataset	Performance Measure	Result
2019	Logistic Regression	22, 854 participants from a retrospective cohort	Accuracy	82.6%
	Ridge Regression			83.3%
2019	Second Glance framework	1,504 independent WCE Images	ROC-AUC	0.9235
2020	Extraction of Handcrafted Features and Deep features and fused them and apply machine learning classifiers.	Kvasir, CVC-ClinicDB, and ETIS-LaribPolypDB	Accuracy	96.5%
2018	Extracted Local-Binary-Pattern features and applied SVM classifier	WCE Independent Images	Accuracy	98.85%
2014	Develop a single matrix for all features and then applied Support Vector Machine (SVM), decision trees and Neural network (NN).	WCE Independent images	Accuracy	92.86% and 93.64%,
2019	1. HSI colour transformation is used to transform colours. 2. After that, the YIQ colour space is used to implement the saliency-based technique. 3. Following that, image fusion is carried out. 4. The retrieved features were then fused using SVD, LBP, and GLCM as the final step. 5. Making use of neural networks.	9 thousand samples of ulcers, bleeding, and healthy WCE Images.	Accuracy	95.5%
2020	Least-square saliency transformation (LSST) technique they proposed was ensued by the probabilistic model-fitting approach. LSST was used to detect the	WCE images that has no pixels-annotation.		

Year	Technique	Dataset	Performance Measure	Result
	set of best initial coefficient vectors.			
2021	Combined histogram oriented gradient features obtained from LBP and passed to extreme machine for learning.	WCE images		
2022	Neural Network	MRI Images	Accuracy	95.5%
2023	Assembled multiple handcrafted features like LBP, DWT and GLCM	Endoscopic Images	Accuracy	98.60%

1.10. Deep Learning Techniques for Gastrointestinal Diseases

In [41], authors showed a deep learning-based approach for stomach diseases like ulcers, bleeding, and polyps' classification. They utilized the transfer learning-based approach and fine-tuned a pre-trained ResNet101 model for feature extraction. Later, they used min-distance as a fitness function and applied a grasshopper approach for feature optimization. The multi-SVM was used for classification. The model achieved an accuracy of 99.13%, which outperformed the latest and state-of-the-art techniques. A fully automated approach for diagnosing stomach infection was created by Khan et al. [42]. To identify stomach infections, a wide variety of features, including handcrafted features and fused features were applied. The primary issue with GI tract infections was that the pattern of the affected area shared a lot of similarities. Khan then unveiled a contemporary CAD that includes handcrafted, fusion, and deep CNN elements. Datasets from Kvasir, CVC-ClinicDB, Private, and ETIS-Lari Polyp were used in this study. Using this dataset, they were able to reach an accuracy of 96.5%, respectively.

Haya et al. [43] established a fully automated method to detect the classification of infection, which is AlexNet and googLeNet to classify ulcers and non-ulcers from the objects. Though the dataset was limited the presented techniques showed a 100% accuracy, respectively. The dataset includes 1875 images containing 1525 cases of ulcers and 250 normal cases. GoogLeNet enhances the features and detects the best features from images and it only works on each layer as a filter. AlexNet has more layers than GoogLeNet, the first layer works on feature extraction to detect high-level features. The authors of [44] proposed the VGGNet model, which was based on CNN (Convolutional Neural Network) to detect gastrointestinal ulcers with the dataset of 854 images and achieved 86.6% accuracy, respectively. Despite the fact that these tests were performed using standard endoscopic images In [45], authors' developed a model that was based on CNN; the dataset consisted of 5360 WCE images having ulcers and erosions and contained merely 440 normal images. The detection accuracy of this method was 90.8%, respectively. Sekuboyina and co-authors in [46] proposed models based on CNN to detect dissimilar forms of lesions in WCE images, like ulcers, bleeding, polyps, and more. The authors distributed images into numerous areas and then applied the model. The work of the author achieved 71% sensitivity and 72% specificity.

Zhang et al. [47] developed a GDPNet model, which was based on CNN for the classification of ailments like ulcers, erosions, and polyps. The achieved accuracy of this model is 88.9%. The authors of [48] proposed a HANet model with a network based on ResNet-34 for the recognition of ulcer ailment in WCE images. The model achieved 91% testing accuracy. The authors showed second-glance detection, which was based on the Convolutional Neural Network [49]. The testing exhibits 0.9469 ROC Curve and AUC. The sensitivity, specificity, and accuracy of the model were 89.71%, 90.48%, and 90.10%, respectively. The authors used the AlexNet network, which was based on CNN to train the database and attained an accuracy, sensitivity, and specificity of 95.16%, 96.80%, and 94.79% of ulcer detection and also AUC value of 0.9805, respectively [50]. However, this method used regular AlexNet architecture, which demonstrated misclassification in low or poor-quality images. The research done by Alaskar et al. [43] used a transfer learning approach and employed two convolutional neural networks, namely GoogLeNet and AlexNet. The authors applied these models to a dataset, which contains 526 images taken from WCE videos. The experiment showed that a high learning-rate of 0.01 does not bring reasonable results for AlexNet and GoogLeNet. Klang et al. [51] experimented on dataset, which contained 7391 images of mucosal ulcers and 10,249 images of normal GI mucosa. This experiment achieved 95.4% accuracy, respectively.

Ozawa et al. built a ROGUE system using a convolutional neural network on 3981 ulcer images [52]. The outcomes presented 0.86 ROC, however, the accuracy was not specified. Lee along with co-authors' developed a Deep Neural Network by using pre-trained models, namely ResNet, VGGNet and, inception. This model used dataset of 220 ulcers, 367 cancers, and 200 normal images [53]. The obtained ROC curve was in the range between 0.85 - 0.95, however, the accuracy was only 77.1%, respectively. A Single Shot Multi-box Detector, which was based on a deep convolutional neural network presented by Aoki, Tomonori et al. was used to train dataset of 5360 WCE ulcer images. Sensitivity, specificity, and accuracy were performance measures and this method achieved a Sensitivity of 88.2%, specificity of 90.9%, and accuracy of 90.8%, respectively [45]. In [54] authors presented a computer-aided system for the detection of ulcers in WCE images. In the proposed technique, after performing preprocessing steps, a MobileNet model, which was trained on the ImageNet dataset was fine-tuned and features were extracted. After the extraction, the Random Forest classifier was applied for the classification of ulcers. The proposed technique of paper, achieved 95.34% recall and 9673% precision. Deep Convolutional Neural Network (CNN) was presented by the authors of [55] for automatic ulcer discrimination on various proportions of augmented datasets containing WCE images in the range of 1000-10000, which included ulcer and non-ulcer images. A thorough analysis of network configuration for a large number of nodes and depth was conducted. The performance was noticeably improved by the four convolutional layers with 3*3 convolutional filters suggested by the architecture. Real-time WCE video frames and freely available WCE datasets were used to create the WCE images. For a variety of fine-tuning parameters, including learning rate, dropout scheme, epochs, activation functions, total layers, and optimizer, the experiment results were subjected to hyper-parameter optimization. In [56] authors proposed a transfer learning approach in which images are preprocessed using Top-Hat and Bottom-Hat filtering and then CLAHE was applied. Then ResNet-50 and ResNet-152 V2 were applied to a given dataset and extracted features from both models were fused. After that, a modified genetic algorithm (GA) was used for the optimization of these fused features. This approach achieved an accuracy of 99.67% respectively. In the study [57], authors applied a contrast enhancement method and applied modified MobileNet-V2 for the classification of gastro ailments and achieved 96.40% results for accuracy. The authors in [58], applied two parallel deep learning models and fused their features, which were optimized using ACO algorithm. This method achieved 96.43% accuracy, respectively. A summary of deep learning based techniques which were used for the prediction of peptic ulcer from endoscopic images dataset [59–63] are shown in Table 4.

Table 4. Summary of Deep Learning Techniques for Peptic Ulcer Prediction

Year	Technique	Dataset	Performance Measure	Result
2020	1. Applied Transfer learning concept in pre-trained ResNet101 model and fine-tune it for feature extraction. 2. Min distance served as a fitness function, and the features were subsequently optimized using the grasshopper approach. 3. The multi-SVM was used for the classification of stomach diseases.	KASVAIR Dataset	Accuray	99.13%
2019	Used AlexNet and googLeNet.	The dataset includes 1875 images containing 1525 cases of ulcers and 250 normal cases.	Accuracy	100%
2018	CNN model based on VGGNet	854 Classic Endoscopy Images	Accuracy	86.6%
2019	CNN model	WCE Dataset – Erosion and Ulcer Images: 5560 Normal Images : 440	Accuracy	90.8%

Year	Technique	Dataset	Performance Measure	Result
2017	Divided images into numerous areas and then applied Convolutional Neural Network	WCE Images	Sensitivity	71%
			Specificity	72%
2017	GDPNet model, which was based on Convolutional Neural Network	WCE Images	Accuracy	88.9%
2019	HANet architecture with ResNet-34	WCE Images	Accuracy	91%
2019	Second glance detection based on deep CNN	WCE Images	ROC-AUC Curve	0.9469
			Sensitivity	89.71%
			Specificity	90.48%
			Accuracy	90.10%
2018	AlexNet convolutional neural network	WCE Images	ROC-AUC Curve	0.9805
			Sensitivity	96.80%
			Specificity	94.79%
			Accuracy	95.16%
2019	GoogleNet and AlexNet are two pre- trained models used	526 WCE images taken from videos	Unsatisfactory results	
2019	Computer-Added-System by applying CNN	3981 ulcer images	ROC	0.86
2019	Deep Network employing pre-trained models from Inception, ResNet and VGGNet	367 cancer cases images, 220 ulcer cases images, and 200 normal cases images	Accuracy	77.1%
			ROC	0.85 – 0.95
2020	Based on a Single-Shot-Multibox-Detector, a deep convolutional neural network system	5360 cases of ulcers	Sensitivity	88.2%
			Specificity	90.9%
			Accuracy	90.8%

Year	Technique	Dataset	Performance Measure	Result
2019	Recurrent attention neural network	WCE images having 600 with diseases and 600 normal images	Accuracy	90.85%
2022	Preprocessed images using top-hat, bottom-hat filtering and CLAHE. Then features of ResNet-50 and ResNet-152 V2 were fused and optimized using modified GA	Kvasir dataset	Accuracy	99.67%
2023	Applied a contrast enhancement method and applied modified MobileNet-V2 for classification of gastro ailments	Kvasir-V2 Dataset	Accuracy	96.40%
2023	Two parallel deep learning models and fused there features which are optimized using ACO algorithm	Kvasir Dataset	Accuracy	96.43%

2. DISCUSSION

With the advancement of DL theory in recent years, several effective deep DL models [64, 65] have developed; which have gained tremendous success in the field of computer vision and other fields. Among these DL models, CNNs have progressed exceptionally well in image processing, which has also been used to analyze a variety of medical pictures. Since 2015, the DL approach has steadily been used for the GI image analysis. However, several current researches are still restricted for the detection, categorization, and segmentation of polyps, haemorrhages, and GI cancer. GI illnesses, on the other hand, have many intraepithelial neoplasia and invasive mucosal lesions, which are regarded as crucial stages of early cancer, and are also worth studying by using the DL approach; however, they have not yet been discussed in the current literature.

A huge number of labeled training datasets are required for the DL approach. AlexNet's [66] training dataset, for example, has 1.2 million samples. It is difficult to gather a large volume of labeled medical picture data due to the high expense of manual labeling by medical specialists and the consideration of patient privacy considerations. Unlike skin, eye, MR, and CT pictures, which are obtained from the body's surface, GI images need an endoscopy, which entails inserting a camera probe inside the patient's body. As a result, acquiring GI image data is more difficult and the use of DL in computer-aided GI diagnosis is severely constrained, demanding, and ineffective. Due to large training data sets, containing more than 0.10 million labeled images, great progress has been obtained in the use of DL in different illnesses, such as brain and skin disorders.

Furthermore, recognized items in nature photographs are frequently colorful and have distinct limits, however, lesions in medical images lack a standardized, regular form, which do not always have distinct boundaries. Given the disparities between natural and medical pictures, models trained on natural images may be ineffective for assessing medical images. Furthermore, the ensuing analysis may be unimpressive if the training data set is insufficient throughout the transfer learning process. The differences between various popular types of medical pictures are lower than those between natural images; if transfer learning is done on a foundation of pre-trained models with medical images, the results may be better than those obtained by directly employing natural image pre-trained models.

For recognition of gastrointestinal diseases from endoscopic images, major problems that are noted in prior literature and still needs improvement are indicated below:

- Issue of intra-class and inter-class similarity of gastro diseases.
- Lightening issue in endoscopic procedure due to which images exhibits weak contrast.
- Improvement of model performance in terms of accuracy.
- Variation in shape and size of one disease, which make it difficult to recognize.
- Unwanted artifacts in endoscopic images are present like textual information, which is important for doctors.

2.1. Conclusion

The current study aims to investigate the GI tract (Gastrointestinal tract) domain. Recently, many case studies and models have been developed for the detection of peptic ulcer by incorporating artificial intelligence (AI) techniques. Some researchers employed machine learning techniques, while others chose a deep learning-based technique. If we talk about the dataset regarding Wireless Capsule Endoscopy (WCE) images, most of the researchers used their own developed dataset which depicts that there is a need to develop techniques for publically available datasets of WCE images. Moreover, the classification of intra-class variations of peptic ulcer is a deficient area in which the attention of researchers is crucially required. In terms of performance measures, most of the researchers used accuracy to develop models, which also show sensitivity, specificity, f-measure, and confusion matrix. It is also a need of time to test the generated model on real datasets so that overfitting, underfitting, and accuracy can be justified.

REFERENCES

1. Prabhu V, Shivani A. An overview of history, pathogenesis and treatment of perforated peptic ulcer disease with evaluation of prognostic scoring in adults. *Ann Med health Sci Res.* 2014;4(1):22–29. https://doi.org/10.4103/2141-9248.126604
2. Bhatti A. 3 common types of ulcers. https://bhattigi.com/3-common-types-of-ulcers/
3. Ojala T, Pietikäinen M. Unsupervised texture segmentation using feature distributions. *Pattern Recognit.* 1999;32(3):477–486. https://doi.org/10.1016/S0031-3203(98)00038-7

4. Gevers T, Smeulders AW. Color-based object recognition. *Pattern Recognit*. 1999;32(3):453–464. https://doi.org/10.1016/S0031-3203(98)00036-3

5. Ahmed M. Peptic ulcer disease. In: Qi X, Koruth S, eds. *Digestive System*. IntechOpen; 2019. https://doi.org/10.5772/intechopen.86652

6. O'connor HJ. The role of Helicobacter pylori in peptic ulcer disease. *Scand J Gastroenterol*. 1994;29;11–15. https://doi.org/10.3109/00365529409105354

7. World Health Organization. Death by sex and age group for a selected country or area and year. WHO website. https://platform.who.int/mortality/themes/theme-details/topics/indicator-groups/indicator-group-details/MDB/peptic-ulcer-disease. Accessed April 4,2023

8. Dey N, Ashour AS, Shi F, Sherratt RS. Wireless capsule gastrointestinal endoscopy: Direction-of-arrival estimation based localization survey. *IEEE Rev Biomed Eng*. 2017;10:2–11. https://doi.org/10.1109/RBME.2017.2697950

9. Yeh JY, Wu TH, Tsai WJ. Bleeding and ulcer detection using wireless capsule endoscopy images. *J Softw Eng Appl*. 2014;7(5):e46055. https://doi.org/10.4236/jsea.2014.75039

10. Arnott ID, Lo SK. The clinical utility of wireless capsule endoscopy. *Dig Dis Sci*. 2004;49:893–901.

11. Sainju S, Bui FM, Wahid KA. Automated bleeding detection in capsule endoscopy videos using statistical features and region growing. *J Med Syst*. 2014;38:e25.

12. Lehmann TM, Gonner C, Spitzer K. Survey: Interpolation methods in medical image processing. *IEEE Trans Med Imag*. 1999;18(11):1049–1075. https://doi.org/10.1109/42.816070

13. Khan TH, Wahid KA. White and narrow band image compressor based on a new color space for capsule endoscopy. *Image Commun*. 2014;29(3):345–360. https://doi.org/10.1016/j.image.2013.12.001

14. Gu Y, Xie X, Li G, et al. Design of endoscopic capsule with multiple cameras. *IEEE Trans Biomed Circuits Syst*. 2014;9(4):590–602. https://doi.org/10.1109/TBCAS.2014.2359012

15. Turcza P, Duplaga M. Low power FPGA-based image processing core for wireless capsule endoscopy. *Sens Actuators A*. 2011;172(2):552–560. https://doi.org/10.1016/j.sna.2011.09.026

16. Albisser Z. *Computer-Aided Screening of Capsule Endoscopy Videos* [master's thesis]. University of Oslo; 2015. http://urn.nb.no/URN:NBN:no-51684

17. National Institute of Diabetes and Digestive and Kidney Diseases. Your digestive system & how it works. NIDDK Website. https://www.niddk.nih.gov/health-information/digestive-diseases/digestive-system-how-it-works. Updated January 1, 2022.

18. Borgli H, Thambawita V, Smedsrud PH, et al. HyperKvasir, a comprehensive multi-class image and video dataset for gastrointestinal endoscopy. *Sci Data*. 2020;7(1):e283. https://doi.org/10.6084/m9.figshare.12759833

19. Bernal, J, Aymeric H. Miccai endoscopic vision challenge polyp detection and segmentation.

https://endovissub2017-giana.grand-challenge.org/home/

20. Bernal J, Sánchez FJ, Fernández-Esparrach G, Gil D, Rodríguez C, Vilariño F. WM-DOVA maps for accurate polyp highlighting in colonoscopy: validation vs. saliency maps from physicians. *Comput Med Imaging Graph*. 2015;43:99–111. https://doi.org/10.1016/j.compmedimag.2015.02.007

21. Bernal J, Sánchez J, Vilarino F. Towards automatic polyp detection with a polyp appearance model. *Pattern Recognit*. 2012;45(9):3166–3182. https://doi.org/10.1016/j.patcog.2012.03.002

22. Tajbakhsh N, Gurudu SR, Liang J. Automated polyp detection in colonoscopy videos using shape and context information. *IEEE Trans Med Imaging*. 2015;35(2):630–44. https://doi.org/10.1109/TMI.2015.2487997

23. Jha D, Smedsrud PH, Riegler MA, et al. A segmented polyp dataset. Paper presented at: 26th International Conference Proceedings, Part II; January 5–8, 2020; Daejeon, South Korea. https://doi.org/10.1007/978-3-030-37734-2_37

23. Gastrolab the gastrointestinal site. Gastro Lab Website. http://www.gastrolab.net/index.htm. Accessed January 4,2022.

24. Bernal J, Aymeric H. Gastrointestinal image analysis. Endoscopic Vision Web site. https://endovissub2017-giana.grand-challenge.org/home/. Updated January 4, 2021.

25. Angermann Q, Bernal J, Sánchez-Montes C, et al. Towards real-time polyp detection in colonoscopy videos: adapting still frame-based methodologies for video sequences analysis. Paper presented at: 4th International Workshop, CARE 2017, and 6th International Workshop, CLIP 2017, Held in Conjunction with MICCAI 201; September 14, 2017; Québec City, Canada. https://doi.org/10.1007/978-3-319-67543-5_3

26. Bernal JJ, Histace A, Masana M, et al. Polyp detection benchmark in colonoscopy videos using gtcreator: A novel fully configurable tool for easy and fast annotation of image databases. Paper presented at: Proceedings of 32nd CARS Conference; January 20, 2018; Berlin, Germany. https://hal.archives-ouvertes.fr/hal-01846141

27. Ali S, Zhou F, Daul C, et al. Endoscopy artifact detection (EAD 2019) challenge dataset. *ArXiv Preprint*. 2019. https://doi.org/10.48550/arXiv.1905.03209

28. Baxter NN, Sutradhar R, Forbes SS, Paszat LF, Saskin R, Rabeneck L. Analysis of administrative data finds endoscopist quality measures associated with postcolonoscopy colorectal cancer. *Gastroenterology*. 2011;140(1):65–72. https://doi.org/10.1053/j.gastro.2010.09.006

29. Singh A, Thakur N, Sharma A. A review of supervised machine learning algorithms. Paper presented at: 3rd International Conference on Computing for Sustainable Global Development (INDIACom); 16–18 March 2016; New Delhi, India.

30. Wong GL, Ma AJ, Deng H, et al. Machine learning model to predict recurrent ulcer bleeding in patients

with history of idiopathic gastroduodenal ulcer bleeding. *Aliment Pharmacol Ther*. 2019;49(7):912–918. https://doi.org/10.1111/apt.15145

31. Wang S, Xing Y, Zhang L, Gao H, Zhang H. Second glance framework (secG): Enhanced ulcer detection with deep learning on a large wireless capsule endoscopy dataset. *Int Conf Pattern Recognit*. 2019;11198:170–176. https://doi.org/10.1117/12.2540456
32. Majid A, Khan MA, Yasmin M, Rehman A, Yousafzai A, Tariq U. Classification of stomach infections: A paradigm of convolutional neural network along with classical features fusion and selection. *Microsc Res Tech*. 2020;83(5):562–576. https://doi.org/10.1002/jemt.23447
33. Bchir O, Ismail M, AL_Aseem N. Empirical comparison of visual descriptors for ulcer recognition in wireless capsule endoscopy video. *Comput Sci Inf Technol.* 2018;28:1–9. https://doi.org/10.5121/csit.2018.80501
34. Liaqat A, Khan MA, Shah JH, Sharif M, Yasmin M, Fernandes SL. Automated ulcer and bleeding classification from WCE images using multiple features fusion and selection. *J Mech Med Biol*. 2018;18(4):e1850038. https://doi.org/10.1142/S0219519418500380
35. Khan MA, Rashid M, Sharif M, Javed K, Akram T. Classification of gastrointestinal diseases of stomach from WCE using improved saliency-based method and discriminant features selection. *Multimed Tools Appl*. 2019;78:27743–27770. https://doi.org/10.1007/s11042-019-07875-9
36. Kundu AK, Fattah SA, Wahid KA. Least square saliency transformation of capsule endoscopy images for PDF model based multiple gastrointestinal disease classification. *IEEE Access*. 2020;8:58509–58521. https://doi.org/10.1109/ACCESS.2020.2982870
37. Rathnamala S, Jenicka S. Automated bleeding detection in wireless capsule endoscopy images based on color feature extraction from Gaussian mixture model superpixels. *Med Biol Eng Comput*. 2021;59:969–987. https://doi.org/10.1007/s11517-021-02352-8
38. Sharafeldeen A, Elsharkawy M, Khaled R, et al. Texture and shape analysis of diffusion-weighted imaging for thyroid nodules classification using machine learning. *Med Phys*. 2022;49(2):988–999. https://doi.org/10.1002/mp.15399
39. Al-Mekhlafi ZG, Senan EM, Alshudukhi JS, Mohammed BA. Hybrid techniques for diagnosing endoscopy images for early detection of gastrointestinal disease based on fusion features. *Int J Intell Syst.* 2023;e8616939. https://doi.org/10.1155/2023/8616939
40. Khan MA, Javed K, Khan SA, et al. Human action recognition using fusion of multiview and deep features: an application to video surveillance. *Multimed Tools Appl*. 2020:1–27. https://doi.org/10.1007/s11042-020-08806-9
41. Majid A, Khan MA, Yasmin M, Rehman A, Yousafzai A, Tariq U. Classification of stomach infections: A paradigm of convolutional neural

network along with classical features fusion and selection. *Microsc Res Tech*. 2020;83(5):562–576. https://doi.org/10.1002/jemt.23447

42. Alaskar H, Hussain A, Al-Aseem N, Liatsis P, Al-Jumeily D. Application of convolutional neural networks for automated ulcer detection in wireless capsule endoscopy images. *Sensors*. 2019;19(6):e1265. https://doi.org/10.3390/s19061265

43. Sun JY, Lee SW, Kang MC, Kim SW, Kim SY, Ko SJ. A novel gastric ulcer differentiation system using convolutional neural networks. Paper presented at: IEEE 31st International Symposium on Computer-Based Medical Systems (CBMS); 18–21 June 2018; Karlstad, Sweden. https://doi.org/10.1109/CBMS.2018.00068

44. Aoki T, Yamada A, Aoyama K, et al. Automatic detection of erosions and ulcerations in wireless capsule endoscopy images based on a deep convolutional neural network. *Gastrointest Endosc*. 2019;89(2):357–363. https://doi.org/10.1016/j.gie.2018.10.027

45. Sekuboyina AK, Devarakonda ST, Seelamantula CS. A convolutional neural network approach for abnormality detection in wireless capsule endoscopy. Paper presented at: IEEE 14th International Symposium Biomedical Imaging; 2017; Melbourne, Australia. https://doi.org/10.1109/ISBI.2017.7950698

46. Zhang X, Hu W, Chen F, et al. Gastric precancerous diseases classification using CNN with a concise model. *PLOS ONE*. 2017;12(9):e0185508. https://doi.org/10.1371/journal.pone.0185508

48. Wang S, Xing Y, Zhang L, Gao H, Zhang H. Deep convolutional neural network for ulcer recognition in wireless capsule endoscopy: experimental feasibility and optimization. *Comput Math Methods Med*. 2019;2019:e7546215. https://doi.org/10.1155/2019/7546215

48. Wang S, Xing Y, Zhang L, Gao H, Zhang H. A systematic evaluation and optimization of automatic detection of ulcers in wireless capsule endoscopy on a large dataset using deep convolutional neural networks. *Phys Med Biol*. 2019;64(23):e235014.

49. Fan S, Xu L, Fan Y, Wei K, Li L. Computer-aided detection of small intestinal ulcer and erosion in wireless capsule endoscopy images. *Phys Med Biol*. 2018;63(16):e165001. https://doi.org/10.1088/1361-6560/aad51c

50. Soffer S, Klang E, Shimon O, et al. Deep learning for wireless capsule endoscopy: a systematic review and meta-analysis. *Gastrointest Endosc*. 2020;92(4):831–839. https://doi.org/10.1016/j.gie.2020.04.039

51. Ozawa T, Ishihara S, Fujishiro M, et al. Novel computer-assisted diagnosis system for endoscopic disease activity in patients with ulcerative colitis. *Gastrointest Endosc*. 2019;89(2):416–421. https://doi.org/10.1016/j.gie.2018.10.020

52. Lee JH, Kim YJ, Kim YW, et al. Spotting malignancies from gastric endoscopic images using deep learning. *Surg Endosc*. 2019;33:3790–3797.

53. Ellahyani A, Charfi S. Computer-aided diagnosis system for ulcer detection in wireless capsule endoscopy images. *J Phys*. 2021;1743(1):e012016.

54. Vani V, Prashanth KM. Ulcer detection in wireless capsule endoscopy images using deep CNN. *J King Saud Univ Comp Infor Sci*. 2022;34(6):3319–3331. https://doi.org/10.1016/j.jksuci.2020.09.008

55. Masmoudi Y, Ramzan M, Khan SA, Habib M. Optimal feature extraction and ulcer classification from WCE image data using deep learning. *Soft Comput*. 2022;26(16): 7979–7992. https://doi.org/10.1007/s00500-022-06900-8

56. Noor MN, Nazir M, Khan SA, Song OY, Ashraf I. Efficient gastrointestinal disease classification using pretrained deep convolutional neural network. *Electronics*. 2023;12(7):e1557. https://doi.org/10.3390/electronics12071557

57. Alhajlah M, Noor MN, Nazir M, Mahmood A, Ashraf I, Karamat T. Gastrointestinal diseases classification using deep transfer learning and features optimization. *Comput Mater Contin*. 2023; 75(1):2227–2245.

58. The gastrolab image gallery. Gastrolab Web site. http://www.gastrolab.net/index.htm. Accessed January 4, 2022.

59. World Endoscopy Organization WEO clinical endoscopy atlas. World Endoscopy Organization Webs Site. http://www.endoatlas.org/index.php. Accessed January 1, 2022.

60. Esophagus stomach duodenum& ampulla capsule endoscopy inflammatory bowel disease colon ileum miscellaneous. The atlas of Gastrointestinal Endoscopy Website. http://www.endoatlas.com/atlas_1.htm. Accessed December 11,2022.

61. El salvador atlas of gastrointestinal video endoscopy. Gastro Intestinal Atlas Website. http://www.gastrointestinalatlas.com/index.html. Accessed January 2, 2022.

62. Gastrointestinal lesions in regular colonoscopy dataset. Departamento de Electrónica Website. http://www.depeca.uah.es/colonoscopy_dataset/. Accessed December 12, 2022.

63. Noor MN, Nazir M, Ashraf I, Almujally NA, Aslam M, Fizzah Jilani S. GastroNet: A robust attention-based deep learning and cosine similarity feature selection framework for gastrointestinal disease classification from endoscopic images. *CAAI Transac Intell Technol*. 2023:1–14. https://doi.org/10.1049/cit2.12231

64. Nouman Noor M, Nazir M, Khan SA, Ashraf I, Song OY. Localization and Classification of Gastrointestinal Tract Disorders Using Explainable AI from Endoscopic Images. *Appl Sci.* 2023;13(15)e9031. https://doi.org/10.3390/app13159031

65. Yu W, Yang K, Bai Y, Xiao T, Yao H, Rui Y. Visualizing and comparing AlexNet and VGG using deconvolutional layers. Paper presented at: 33rd International Conference on Machine Learning; June 19–24, 2016; New York, USA.