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Systematic Exploration Using Intelligent Computing Techniques for Clinical Diagnosis of Gastrointestinal Disorder: A Review

Rohit Srivastava[1*] and Manish Madhava Tripathi[2]

[1]Department of Computer Science and Engineering, Integral University, Lucknow, Uttar Pradesh, 226026, India;
[2]Department of Computer Science and Engineering, Integral University, Lucknow, Uttar Pradesh, 226026, India

E-mail/Orcid Id:

RS, rohitcss710@gmail.com, https://orcid.org/0000-0002-5045-6351; MMT, mmt@iul.ac.in, https://orcid.org/0000-0003-3441-5733

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Abstract: In today's era, the growing ratio of Gastrointestinal (GI) diseases in human beings has become a crucial point of notice and must be diagnosed as early as possible. There are various methods to diagnose abdomen-related problems using medical imaging techniques like ultrasound, endoscopy, Colonoscopy, abdominal CT scan and digital X-ray, etc. Endoscopy is one of the most efficient medical imaging techniques for diagnosing gastrointestinal (GI) diseases. Manual diagnosis of endoscopic images may have a possibility of committing mistakes in properly detecting gastrointestinal disorders because tiny particles are involved in endoscopic images and may be responsible for critical disorders. However, manual diagnosis may ignore such information because of less efficiency of vision and observation. To avoid such problems, various models based on soft computing and neuro-fuzzy techniques have been proposed to detect and classify various gastrointestinal disorders. In this article, the authors propose a systematic review of previous research that has been carried out using intelligent computing methods. Here, various conventional approaches are discussed and compared. This review research shows performance limitations due to complex data models, heterogeneous datasets and the absence of intelligent feature selection methods in diagnosing gastrointestinal disorders.

Introduction

Endoscopy is considered a nonsurgical phenomenon for diagnosing the digestive tract of human beings. It utilizes a flexible tube with a light camera and an endoscope so the doctor can see the pictures of the digestive tract on a colored display device (MacIntosh et al., 2013). In upper abdominal endoscopy, the endoscope is easily swallowed through the mouth and throat and passed into the esophagus, allowing the Diagnostic person to check the esophagus, stomach, and the small intestine's upper area. Similarly, in the Colonoscopy, depending on the distance where the call is needed to be diagnosed, the endoscope must be passed through the rectum to the enormous intestine for diagnosis of the area of the intestine (Siau et al., 2019). Colonoscopies are also considered as sigmoidoscopy.

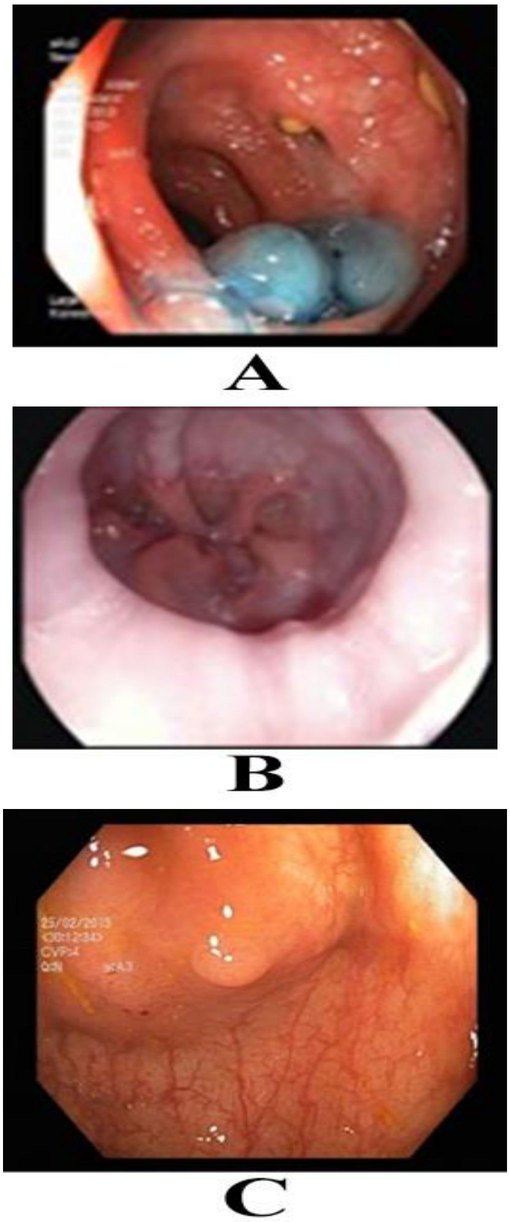
An upper endoscopy, sometimes called an upper gastrointestinal endoscopy, is a procedure that uses a camera to examine the upper digestive tract (Carpentier et al., 2016). This technique is aided by a tiny camera that is fixed to the end of a long, flexible tube. A gastroenterologist, a doctor specialising in digestive system disorders, uses endoscopy to identify and occasionally treat issues affecting the upper portion of the digestive system (Bisschops et al., 2016). Another specific type of endoscopy, known as endoscopic retrograde cholangiopancreatography or ERCP can take pictures of the pancreas, gallbladder and other parts of the abdomen related to it. It Can also be applied to the placement of stents and biopsies (Teh et al., 2015).

During the complete observation through Colonoscopy, almost half an hour is consumed, but generally, it depends on the number of samples required for the treatment and accurate diagnosis (Kim et al., 2015). The cleanness of the lower intestine is also a factor affecting the total duration of the process. The

*Corresponding Author: rohitcss710@gmail.com

patient needs to lie on the bed on his left side, and a sedative drug is inserted before the process through the intravenous line (IV) (Lee et al., 2014). Further, an endoscope is inserted into the rectum of the patient, which may cause pressure and cramping, and the patient may feel pain.

The endoscope sends images of the colon on a video screen. The images can be printed out as a reminder of the investigation. This technique has various possible treatments like Biopsies (tissue samples) and polyp removal (Koeppe et al., 2013). The process is similar to a Colonoscopy, but it is performed from the upper part of the body to investigate upper gastrointestinal (GI) disorders. After the completion, the patient needs time to recuperate. The patient may feel discomfort soon after the endoscopic observation because of trapped air (Ichimasa et al., 2014). He might get some comfort by changing his posture and breathing out. The patient needs to wait for 24 hours after sedation.



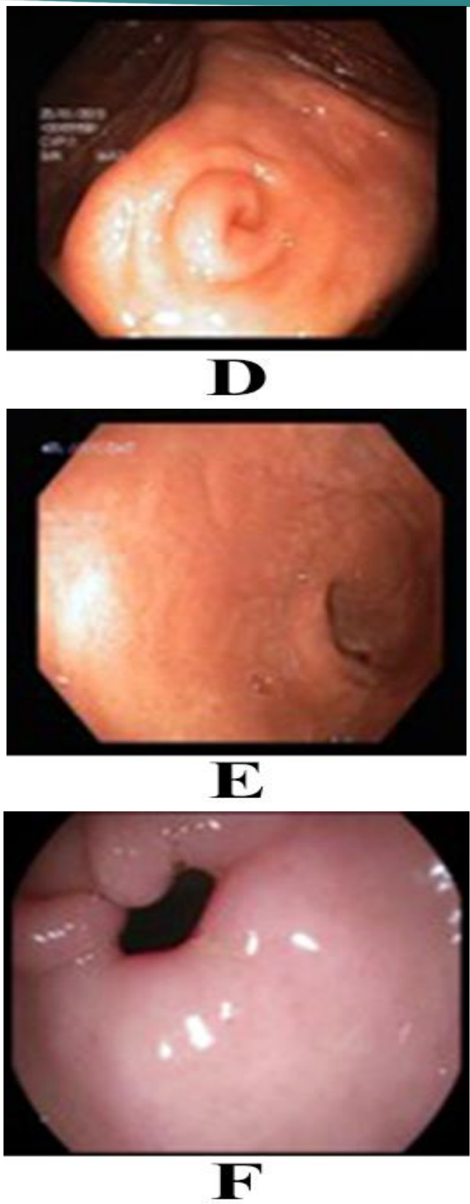


Figure 1. Images captured by endoscopy for (a) dyed-lifted polyps, (b) esophagus, (c) polyps, (d) normal cecum, (e) normal pylorus and (f) ulcerative-colitis (Adapted from Kvasir v2 dataset).

Role of Intelligent computing in diagnosis of Gastrointestinal disorders

Robots are now capable of learning, understanding, and detecting with skills that are equivalent to those of humans thanks to a combination of several technologies known as artificial intelligence (AI). Artificial intelligence (AI) technology will enhance human skills, provide robots with genuine autonomy, reduce errors, and increase output and efficiency in the future (Kumagai et al., 2015). Although there seem to be countless imaginative and original applications for artificial intelligence (AI), cautious optimism may be the best approach given the constraints of machine learning. AI is also used in medicine to improve patient care by speeding up processes and achieving greater accuracy for the best possible patient care (Ono et al., 2015).

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AI based on deep learning has been used to identify and classify images in various medical settings, including gastrointestinal endoscopy. To give endoscopic diagnoses and prognostications of various digestive disorders, the field of gastrointestinal endoscopy uses image processing and a range of gastrointestinal endoscopic device systems (Ruff et al., 2014, Wang et al., 2015). AI-based endoscopic systems can precisely diagnose and provide crucial information on gastrointestinal pathology based on their training and validation. These technologies have the potential to streamline, accelerate, improve dependability, and reduce inter-observer variability in gastroenterology practices in the following years. However, it is unrealistic that these technologies will replace gastrointestinal endoscopists as the decision-making authority. In this work, we also investigate the growing application of AI in gastrointestinal endoscopy (Abraham et al., 2015; Mabe et al., 2017)

Table 1. Review Criteria.

Parameters	Inclusion Criteria	Exclusion Criteria
Publication year	2013-2023	Before 2013
Disease	Gastrointestinal Disorders	Others
Pre-processing	Yes	No
Learning/Training approaches	Supervised Learning	Unsupervised methods
Train/Test ratio	70-30 80-20	Others
Performance metrices	Accuracy/precision/Recall/Error/F-measure	Not available
Dataset	UCI/Kaggle	Others/ collected Privately

Significance of the Systematic Literature Review

A systematic literature review is a research process that involves gathering, assessing, and synthesizing current research papers and relevant literature on a specific topic or research issue in a systematic manner. Its primary purpose is to offer a full grasp of the present level of knowledge on a specific subject. It assists in informing evidence-based decision-making in a variety of sectors, including medical, public health, education and social sciences. The systematic method reduces bias and subjectivity by adopting explicit criteria for research selection, data extraction, and quality evaluation. Systematic reviews can show gaps in previous research, suggesting areas that require additional inquiry. This can direct future research objectives and queries.

Motivation

Nowadays, medical imaging plays a vital role in diagnosing critical diseases and abnormalities in human bodies (Gautam et al., 2020; Haloi et al., 2023; Jain et al., 2023; Bisgin et al., 2023). Generally, it is performed manually by medical experts, which may cause significantly fewer mistakes and carelessness and may initiate severe diseases. To overcome such problems, intelligent computing approaches were applied for efficient diagnosis at minimum cost and maximum efficiency. This is the main factor that motivated me to perform the systematic review for finding research gaps, which may be referred to as future research prospects and beneficial for society.

Literature Search Criteria

This paper shows the overall review process conducted on the research papers published in SCI/SCIE/Scopus database over the last ten years. This review generally includes factors like the year of publication, diseases, feature selection/ extraction techniques, learning/ training methodology, pre-processing techniques, test data/train data ratio, performance metrics and dataset acquired for the experimental usage (Niu et al., 2023). The following tabular representation of the statement mentioned above can show the overall flow of the complete review process.

Data Extraction Methods

In this review, the author has gone through almost 453 research papers related to abdominal disorders accessed from reputed journals like Web of Science, Scopus, PubMed etc. and selected 60 articles for the analysis and risk management of gastrointestinal diseases using intelligent computing methods, machine learning or deep

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learning techniques. The complete flow of the review is shown in the diagram below, which includes the filter criteria for selecting and deselecting the research articles related to abdominal disorders.

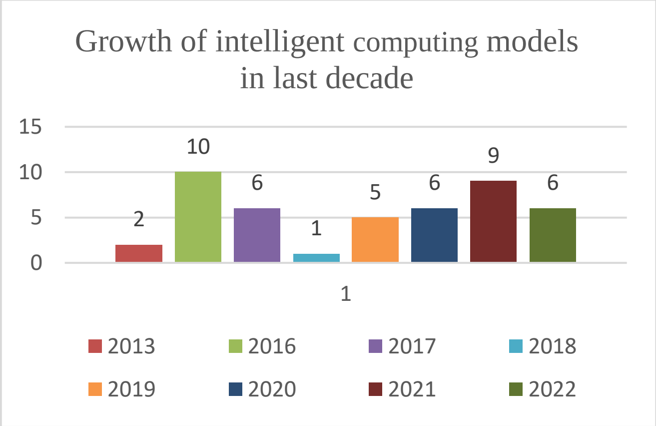

Figure 2. Timeline growth of AI applications in the prediction of GI disorders

In the above figure, the author has shown the growth ratio of machine learning and deep learning techniques for diagnosing and predicting GI diseases in the past ten years. From the above scenario, machine learning techniques were highly applied from 2016 to 2017, while deep learning approaches were used from the beginning of 2018. It shows the significance of intelligent computing for prediction in gastrointestinal (GI) disorders.

Here, the author has represented a systematic review showing the detection of GI disorders using various intelligent computing approaches. Various parameters are applied for selecting the specific article, primarily focusing on their performance metrics and the authenticity of dataset collection. As mentioned below in Figure 3, the selection criteria of articles are shown based on various parameters mentioned in Table 1.

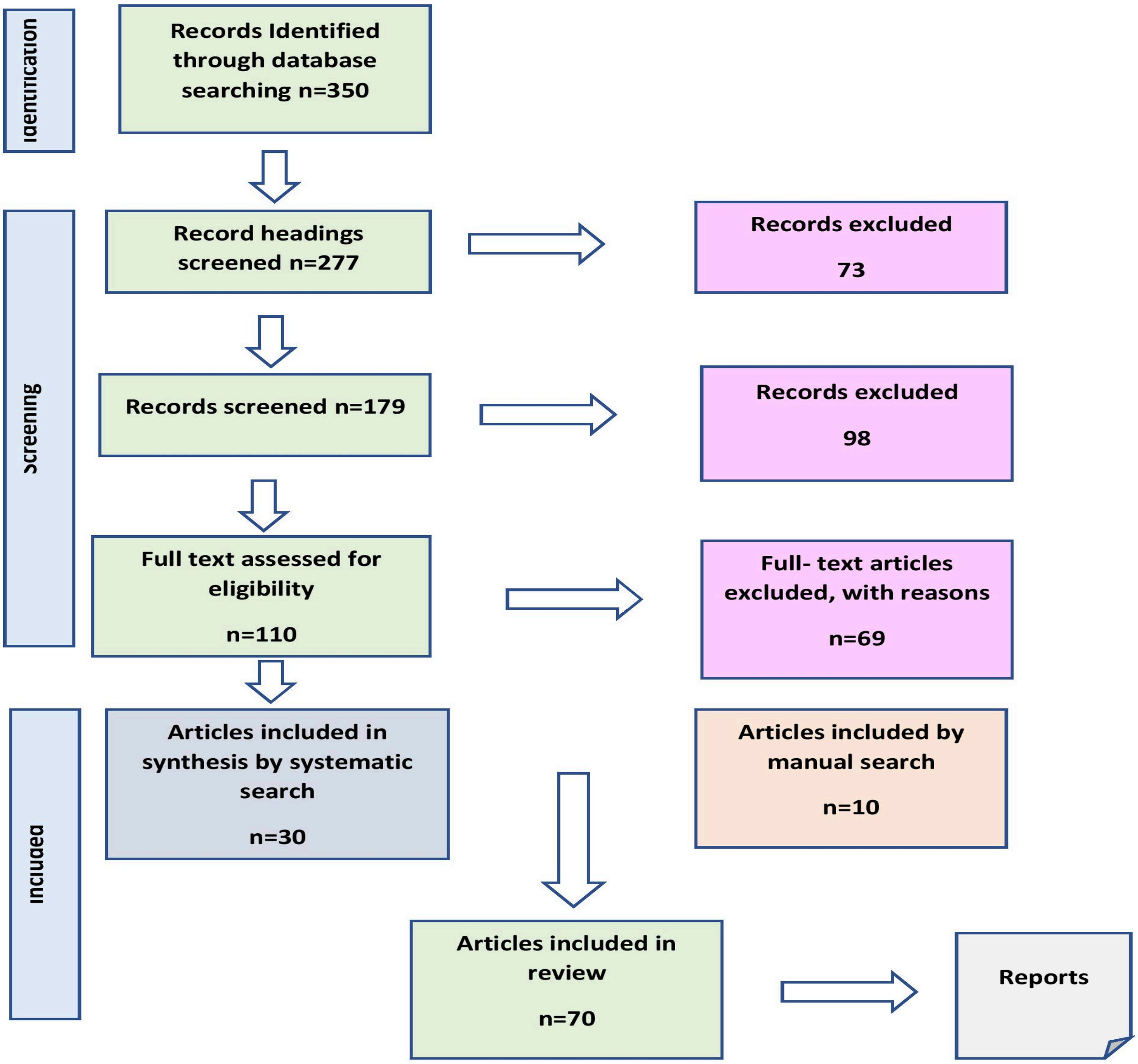

Figure 3. PRISMA dataflow model

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Literature Review

This paper conducts a systematic analysis by reviewing the body of research from the past decade that has employed intelligent computing approaches. The review encompasses the increasing adoption of deep learning and machine learning in various applications. It includes a comparative examination of the various methods employed for precise disease prediction, comparing the outcomes with those from previous studies and highlighting the limitations of the methodologies used for prediction. Tables 3 and 4 present comprehensive comparisons of deep learning and machine learning techniques, respectively, while Table 2 shows intelligent computing methods applied to diagnose GI disorders in the current year.

Latest Application of Intelligent computing techniques used to detect GI disorders

Sharma et al.,2023, proposed a model using n-fold cross-validation; many CNN models (baseline model and those that included transfer learning, such as VGG16, InceptionV3, and ResNet50) were trained on the KVASIR benchmark image dataset, which contained pictures taken inside the GI tract. The dataset includes photos of the healthy colon and three disease states: esophagitis, ulcerative colitis, and polyps. Using the weights from the ResNet50 pre-trained model, the CNN model produced the best results, averaging about 99.80% accuracy on the training data.

Alhajlah et al., 2023, suggested a method for feature extraction based on the Mask Recurrent-Convolutional Neural Network (R-CNN) and optimized pre-trained ResNet-50 and ResNet-152 networks. Using Mask R-CNN, the region of interest is first identified. This information is then used to build refined models via transfer learning. Fine-tuned models are employed to extract features, which are then fused using a serial technique. Furthermore, the optimal feature selection from the fused feature vector has also been selected by an enhanced Ant Colony Optimization (ACO) algorithm. Machine learning techniques are ultimately used to classify the best-selected features. Using the publicly accessible dataset, the experimental procedure produced an enhanced accuracy of 96.43%.

Ghaleb et al., 2023, proposed a model with different techniques to diagnose the endoscopic images using VGG-16 with SVM and Densenet-121 with SVM. Further, an artificial neural network (ANN) was developed using the combined features obtained from Densenet-121 and VGG-16. Again, features fusion with handcrafted features and Densenet-121 was done, and this approach provided an accuracy of 98.9%, sensitivity of 98.7%, and specificity of 98.69%.

Mehedi et al., 2023, proposed a model to evaluate the performance of wireless capsule endoscopy in the diagnosis of GI disorders by developing a spherical-shaped capsule of size 13.8 mm diameter to intelligently capture and observe the 3D images of GI tract. It was found very helpful in providing relief to the patients while inserting the capsule inside the GI tract. It also provided a better observation of images, and the complete process was carried out using COMSOL and MATLAB software.

Mohapatra et al. (2023) gave an intelligent computing approach for the accurate diagnosis of Barret's Esophagitis, haemorrhoids, polyps and ulcerative colitis by applying convolutional neural network (CNN) and Empirical wavelet transform (EWT) over hyper Kvasir dataset. The proposed framework provided an accuracy of 96.65% and a Matthews Correlation coefficient (MCC) of 92.98.

Table 2. Current Applications of intelligent models in the detection of GI disorders.

Reference	Disease	Dataset	Technique	Result	Future Scope
Sharma et al., 2023	Ulcerative colitis	Kvasir	Resnet-50	Accuracy 99.80%	The model can be upgraded by applying optimization approaches
Alhajlah et al., 2023	Polyps etc.	Kvasir	Recurrent-Convolutional Neural Network (R-CNN) Ant colony optimization ResNet-50 ResNet-152	Accuracy 96.43%	The model can be generalized for other medical imaging diagnosis techniques
Ghaleb et al., 2023	Barret’s Esophagitis	Kvasir	VGG-16 +SVM Densenet 121+ SVM	Accuracy 98.90%	Model can be upgraded
Mohpatra et al., 2023	Barret’s Esophagitis etc.	Hyper Kvasir	CNN and EWT	Accuracy 96.65%	Accuracy can be improved

Deep Learning applications in diagnostic gastrointestinal endoscopy

In the following table, deep learning has played a vital role in diagnosing GI disorders using endoscopic images. Various GI diseases are diagnosed by developing intelligent models using endoscopic images for upper and lower GI disorders. In the table below, various deep learning models are applied over different endoscopic datasets obtained from reputed data repositories to predict diseases accurately. The importance of deep learning models is mentioned, along with their accuracy, sensitivity, and specificity results for predicting different GI disorders. This table includes the limitations of those models as mentioned in their future scope. This table also includes the growth of applications of deep learning techniques for prediction. It can show multiple intelligent computing models applied to different diseases in a single view.

The above analysis shows that almost 25 %, 22 % VGG net, and 24% CNN are applied in various pre-trained models and dedicated models developed for accurate prediction. 12 % Googlenet is also applied to classify multiple GI disorders for different stages and situations. Apart from this, other approaches like Densenet, Capsnet and Alexnet are also applied in some of the cases, and their results are compared with other efficient classifiers.

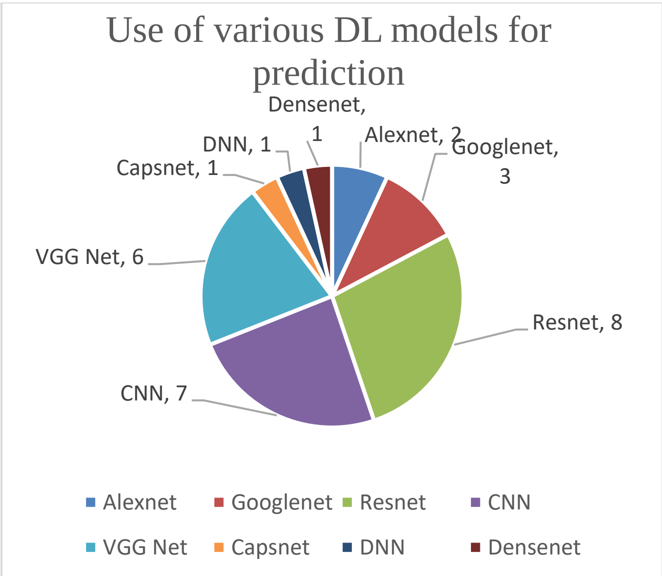

Figure 4. Usage of DL models for prediction of GI disorders

In conclusion, despite deep learning's potential for identifying GI diseases, it's important to consider its drawbacks, especially considering how difficult and important medical diagnosis can be. Collaboration between medical practitioners, data scientists, and ethical experts is crucial to get beyond these restrictions and create trustworthy and efficient diagnostic tools.

Machine Learning applications in diagnostic gastrointestinal endoscopy

The accompanying table shows that machine learning has been crucial in using endoscopic images to diagnose GI illnesses. Many GI diseases can be identified by creating intelligent models with endoscopic pictures for both upper and lower GI illnesses. Multiple machine learning models are applied to various endoscopic datasets gathered from reputable data repositories in the table below for reliable disease prediction. The significance of machine learning models and their outcomes in accuracy, sensitivity, and specificity for predicting various GI illnesses are discussed. The constraints of such models are listed in this table according to their intended use in the future. This table also shows the expansion of machine learning techniques used for prediction and their capacity to provide a peek at multiple outcomes.

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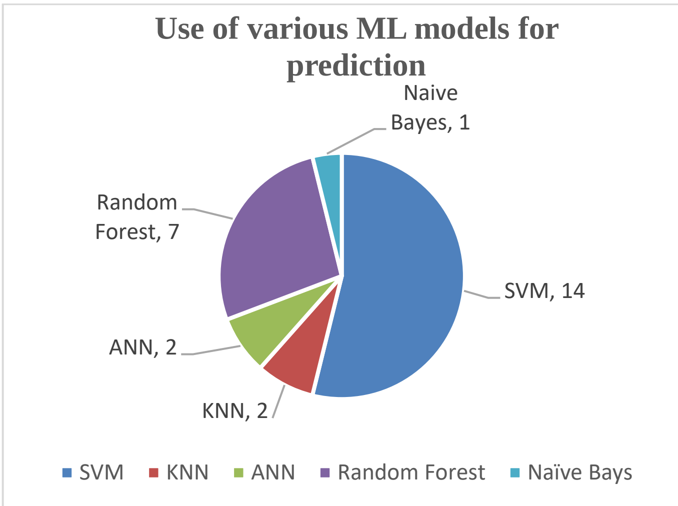

Figure 5. Usage of ML models for the prediction of GI disorders

Table 3. Applications of deep learning models in the detection of various GI disorders.

Year	Disease	References	Technology Used	Procedure	Result	Limitation
2021	Lower gastrointestinal (G.I.) diseases	Hmoud et al., 2021	Pretrained CNN like Alexnet, Googlnet and Resnet 5.0.	Comparative study of the pre-trained model over a dataset of Kvasir containing (5000 images)	ACCURAC 97% Sensitivity 96.8% Specificity 99.20% AUC 99.98%	Advanced Deep Learning are required to be applied to obtain a higher Accuracy
2021	Gastrointestinal Tract Infections	Naz et al., 2021	Classification, segmentation and detection	Comparison of pre-trained model for detection of GI infections	The performance of various pre-trained models was evaluated	Provided a literature-based survey, obtaining better results
2022	Lower gastro-intestine diseases with 23 different classes	Haile et al., 2022	CNN, SVM,	Comparison of the modified version with their own developed model	MCC=0.978 Accuracy= 98%	The feature selection algorithm is required.
2022	Gastritis, ulcer, esophagitis and bleeding	Ayyaz et al., 2022	VGG 19 and Alexnet Fusion Qbic - SVM,fine-KNN	The hybrid method is developed to classify stomach diseases	**VGG 19** Accuracy 98% using Qbic SVM FNR 0.2% AUC-100% FPR-0% **Alexnet** Accuracy 99.8 % FNR-0.4 AUC-1	A comparison of efficient feature selection algorithms is needed
2022	Lower Gastrointestinal Diseases	Fati et al., 2022	A hybrid model containing CNN, SVM, ANN, FNN was applied	A hybrid approach along with deep learning techniques for rapid detection	Accuracy 99.3%, Precision 99.2% Sensitivity-99% Specificity-100% AUC-99.8%	PCA is needed to reduce the dimension of deep features abstracted by CNN model.

2021	Gastro-intestinal (G.I.) Tract Infection	Yang et al., 2021	Creation of a dataset using a mechanical scanning system for capturing microimages	inspection V3, Resnet V2, and Nasnet (mobile) were applied	Accuracy: Inception V3- 90% Nasnset (mobile)- 81% Resnet V2- 88%	In future, a model can be developed to substitute the physical biopsy with a virtual biopsy.
2019	Gastrointestinal Tract Disease	Srivastava et al., 2019	VGG, Resnet and Googlenet and SoftMax classifier	A comparative analysis was done among various pre-trained deep learning models.	VGG-96% Resnet-78.77% Google net- 90.27	Effective for detecting ulcers but not very accurate in the diagnosis of Esophagitis and Normal-polyps
2021	Lower G.I. diseases	Yogapriya et al., 2021	Test time augmentation-on, patching for pre-processing and ImageNet	Classification of Celiac and normal polyps	Accuracy-91.03	Not much effective for Normal polyps.
2022	Inner Surface Infection in G.I. Tract	Ramamurthy et al., 2022	Features of Efficient Net B0 and Effimix were combined	Model that classifies the input gastrointestinal images into 23 classes.	Accuracy - 97.99% F1 score-97% Precision-97% recall-98%	The model can be extended to other gastrointestinal imaging
2020	Barrett's Esophagus (B.E.)	De Groof et al., 2020	Hybrid (ResNet-UNet) model	Five independent datasets of G.I. diseases were checked	**In Data Set 4** (80 patients and photos) Accuracy 89%, Sensitivity 90%, specificity 88%. **In data set 5** (80 patients and pictures) Accuracy, 88% Sensitivity is 93%, specificity 72%.	Accuracy is limited up to 89 % and needs to improve.

2020	Barrett's Esophagus (B.E.)	Hashimoto et al., 2020	Image net and image annotation software for marking of neoplasia region	The proposed model has trained over 458 test pictures (225 with dysplasia and 233 without dysplasia).	Sensitivity 96.4% Specificity 94.2% Accuracy 95.4%	The model is applied over limited data sets, so it should be trained over more extensive data sets.
2019	Barrett's Esophagus (B.E.)	Groof et al., 2019	A uniquely developed model is applied over prospectively collected white light endoscopy (WLE).	Images of 20 patients with non-dysplastic (NDBO) and 40 patients	Sensitivity 95% Specificity 85% Accuracy 92%	The accuracy and size of the dataset are required to be enhanced.
2020	Barrett's Esophagus (B.E.)	Ebigbo et al., 2020	CNN residual net (Res-Net) Deep Lab V.3+	An AI system is developed for classification using random photos from the live video.	Sensitivity 83.7% Specificity 100% Accuracy 89.9%	Requirement for more effective techniques of early EAC in BE detection and characterization
2016	Barrett's Esophagus (B.E.)	Wolfsen et al., 2016	Narrow-band imaging, confocal laser endo-micros-copy, CNN for classification	A model is trained over B dataset of 60 VLE pictures (30 dysplastic and 30 nondysplasti	Sensitivity 90% Specificity 93%	Accuracy should be improved using effective approaches and techniques
2016	Barrett's Esophagus (B.E.)	Swager et al., 2016	Discussion about previous existing techniques	Applications of various latest endoscopic techniques	Use of Chromoendoscopy, Optical and Digital Chromoendoscopy.	Literature survey for detection of BE
2017	Barrett's Esophagus (B.E.)	Swager et al., 2017	Image analysis methods for pre-processing and Machine learning techniques for classification	Based on VLE pictures, an algorithm for detecting BE neoplasia was created with good performance	Sensitivity 90% Specificity 93%	Accuracy should be increased by utilizing sensible strategies and tactics

2020	Barrett's Esophagus (B.E.)	Struyvenberg et al., 2020	Specific CNN was developed for multi-frame classification	Retrospective analysis of ex-vivo VLE pictures from 29 BE patients with and without early neoplasia was performed	Multi-frame AUC 94% Single-frame AUC 83%	Need for effective techniques of early disease detection
2016	Colorectal Cancer	Pan et al., 2016	Analysis is done based on Relative Risk (RR) and Confidence interval (CI) over existing methodologies	provided a literature-based survey on employing pre-made models and methods to get better outcomes.	Relative Risk (RR) 51% Confidence interval (CI) 95%	Required to reduce the Risk factor by applying efficient approaches
2019	Colorectal Cancer	Gupta et al., 2019	Random forest, Support Vector Machine, AdaBoost, and KNN	Given an intelligent model for the detection of colorectal polyps	Accuracy 89% Recall 88%	Accuracy can be improved in future by using better techniques
2017	Colorectal Cancer	Bernal et al., 2017	Comparison of various CNN	An intelligent model using 612 frames from 20 videos (10 infected and 10 normal) is developed.	Comparative Study	N/A
2021	Colorectal neoplasm	Choi et al., 2021	CNN-CAD system compared with Inception V3, Densenet 161 and Resnet 50	A computer-aided diagnostic (CAD) system was created to predict the pathologic histology of colorectal adenoma	sensitivity 77.25%, specificity 92.42%, positive predictive value 77.16%, negative predictive value 92.58%	Required to be trained by applying different settings of images
2021	Colorectal neoplasm	Yao et al., 2021	Self-paced transfer VGG network-based classification method (STVGG)	ImageNet pretraining network parameters are sent to a VGG network over data of 3061 images.	Accuracy 96%	This technique can be used for various imaging studies, including those of the stomach, ears, nose, and throat.

2021	Colorectal neoplasm	Nguyen et al., 2021	VGG 16 Caps Net	High-accuracy algorithm for classifying colorectal tissue.	Accuracy 93.9%	Techniques needed for selecting the best features and optimization approaches
2019	Colorectal neoplasm	Takamatsu et al., 2019	Random forest (RF) classifier	An Automated model was developed for the prediction of cancer tissues, and LNM was created.	Accuracy (RF) 74% AUC (RF) 76%	Accuracy can be enhanced using optimization algorithms
2021	Colorectal neoplasm	Sarwinda et al., 2021	ResNet 18 architecture ResNet 50 architecture	ResNet-18 and ResNet-50 were trained on colon gland images	Accuracy 80% Sensitivity of 87%, Specificity of 83%	Better accuracy is required with less learning overhead
2021	Colorectal neoplasm	Shen et al., 2021	ResNet-50 VGG-19 Inception-V3 Dense-Net	To determine the patches in a WSI (Whole slide image)	Accuracy (ResNet-18) 97.01% (ResNet-50) 97.09% (VGG-19) 97.23% (Inception-V3) 88.33% (Dense-Net) 97.41	Performance acceleration and computational time need to be reduced
2022	Inflammatory bowel disease	Alfarone et al., 2022	White-light Endoscopy, Virtual chromoendoscopy Endocytic Molecular imaging	A study of various A.I. techniques is performed for multiple endoscopic approaches.	A complete Survey for the role of A.I. in the detection of IBD	

2020	Inflammatory bowel disease	Takenaka et al., 2020	Deep Neural Network (DNN)	Deep neural network approach is developed for endoscopic image processing	Accuracy: 90.1% Confidence Interval (C.I.): 95%	Testing is required for higher population
2019	Inflammatory bowel disease	Maeda et al., 2019		Endocytoscopy (EC; 520-fold ultra-magnifying endoscope) was used.		

Table 4. Applications of Machine learning models in the detection of various GI disorders

Year	Disease	References	Technology Used	Procedure	Result	Limitation
2013	Colon Cancer	Yang et al., 2021	Support vector Machine (SVM)	A model applied on 484 zoom endoscopic images	Accuracy 96.9% Sensitivity 97.2% Specificity 96%	A wider data set is required with multiple classes
2016	Polyps	Haefner et al., 2010	SVM and Random Forest (RF)	Intelligent model for Colonoscopy films demonstrating gastrointestinal lesions	Accuracy 82.5% Sensitivity 72.7% Specificity 85.9%	Better Accuracy is required to obtain
2017	Polyps	Mesejo et al., 2016	SVM	AI model that is capable of diagnosing polyps from 100 endoscopic videos	Accuracy 98.7% Sensitivity 98.8% Specificity 98.5%	Training is required on a wider variety of datasets
2018	Polyps	Billah et al., 2017	SVM	AI model for Colonoscopy (466 images) real-time ultra-magnification polyp visualization	Accuracy 96.5 Sensitivity 91% Specificity 98.8%	The larger volume of data is needed for training

2013	Polyps	Mori et al., 2018	SVM	An automated model trained over 1500 images with 1200 infected and 300 normal	Accuracy 95% Sensitivity 91% Specificity 95.2%	Model can be improved further to be trained for various stages of
2016	Barrets's Esophagus	Romain et al., 2013	SVM	Intelligent model for detecting GI tract infections (diagnosis of 44 patients on 100 images)	Sensitivity 86.0% Specificity 87.0%	Higher accuracy is required to be achieved
2022	Colon Cancer	Van et al., 2016	Linear Regression, Naïve Bayes and Random Forest	The model was created for the early-stage detection	Accuracy 98.2%	The model should be trained over the larger dataset
2017	CRC (Colorectal Cancer)	Koppad et al., 2022	SVM	Intelligent model using 2506 non-neoplasm and 2667 adenomas	Accuracy 94.1% Sensitivity 89.4% Specificity 98.9%	Higher accuracy is required
2017	CRC	Takeda et al., 2017	Random Forest (RF)	Intelligent model using 141 (93 infected and 48 normal)	Area Under Curve (AUC) 99% Sensitivity 83.5% Specificity 97.9%	Higher accuracy is required
2016	CRC EMR	Lu et al., 2023	Naïve Bayes (NB)	Model using samples of 38 participants, having 17 healthy and 21	AUC 92.6% Accuracy 91.6%	A larger Dataset is required

2016	CRC	Kop et al., 2016	Random Forest (RF) and 5-fold cross-validation	An intelligent model using 90,000 (89,412 infected and 588 normal) was developed.	Area Under Curve (AUC) 90% Sensitivity 68.0% Specificity 35%	A generalized model is needed to be developed for other diseases
2016	CRC Serum markers of tumours	Hoogendoorn et al., 2016	SVM	An intelligent model using 206 images (86 infected and 120 normal) was developed	Accuracy 82.5% Sensitivity 85.0% Specificity 80.0%	The dataset is required to balance for infected and normal classes
2017	CRC Intestinal microbiota	Zhang et al., 2017	Random forest (RF) Simple logistic	A model using 141 images (93 infected and 48 normal) was developed	Area Under Curve (AUC) 99% Sensitivity 93.5 % Specificity 97.9 %	The model must be trained across a larger dataset.
2016	Tumors	Ai et al., 2016	SVM 4-fold cross-validation	A model was created using 600 images (300 infected and 300 normal).	Accuracy 93.5% Sensitivity 94.0% Specificity 93.0%	trained across a larger dataset.
2016	Tumor	Faghih et al., 2016	SVM 10-fold cross-validation	An automated model was trained using 1800 images (900 infected and 900 normal).	Accuracy 97.3% Sensitivity 97.8% Specificity 96.0%	The model must be balanced for the regular and infected classes in the future.

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In the mentioned above figure, it can be analyzed that almost 60% SVM classifiers have been applied for the prediction of various GI disorders in previous decades, in some cases 25% Random forest and rarely K- nearest neighbor (KNN) and ANN (Artificial neural network) and naive bayes classifier is used for prediction in some different cases and circumstances.

Discussion

As mentioned in Table 2 and Table 3, various limitations of the applied approach, like less availability of data, data imbalance, variability of inter-observations, complexity in GI disorders and sophisticated generalization, may cause the limitation of the performance of the above-developed model. A significant amount of diverse and well-annotated data is needed to create accurate machine-learning models. Such data collection and labelling can be time-consuming and costly. Unbalanced datasets may result from some GI disorders being more uncommon than others. As a result, biased models may favor the dominant class while underperforming the minority class.

Various medical specialists may interpret endoscopic pictures differently, which might result in errors in labelling. The training data may become noisy due to this fluctuation, impacting how well the model performs. Even within the same illness category, gastrointestinal diseases can present with various signs and symptoms. This complexity makes it difficult to create a single model that accurately diagnoses all diseases. Due to variations in illness prevalence, patient demographics, and imaging technology, models developed using data from one group or geographical area may not generalize effectively to other populations. Since many machine learning algorithms, particularly deep learning models, are frequently referred to as researcher-oriented, it might be challenging for medical experts to comprehend how a model arrived at a specific diagnosis. Their confidence in the model's recommendations may suffer because of this lack of interpretability.

In a medical setting, explaining the causes behind a model's choice of a certain diagnosis is essential. This is related to interpretability. Patients and medical professionals need to understand why a certain diagnosis was made to ensure the right treatment choices. Disease patterns and their characteristics may vary according to time and situation. The ability of a model must be to adjust to coming and developing changes in disease, but in general, it may be limited if it is trained on historical data.

Summarizing these drawbacks, it must be carefully studied and addressed to guarantee the safe and successful integration of ML technologies into clinical practice, even though ML holds significant potential for aiding in GI diagnosis. Cooperation between medical experts, data scientists, and regulatory organizations is essential to overcome these obstacles.

Conclusion

Intelligent computing has great significance for predicting and diagnosing GI diseases using endoscopic and Colonoscopy pictures. However, these models have various limitations due to heterogeneous data sets for training and testing. It is difficult to construct such a model capable of predicting all the possible diseases rather than specific ones. Generally, various machine and deep learning approaches are applied to different data sets of multiple diseases. Still, sometimes, the model gets exhausted and fails to make accurate predictions because of noisy and distorted diagnostic images. Even though ML and DL hold tremendous potential for assisting in GI diagnosis, these shortcomings must be carefully examined and addressed to ensure the safe and effective introduction of ML technologies into clinical practice. The proper association between regulatory organizations, data scientists, and medical professionals is also required to overcome these challenges.

Intelligent computing has great significance for predicting and diagnosing GI diseases using endoscopic and Colonoscopy pictures. However, these models have various limitations due to heterogeneous data sets for training and testing. It is pretty difficult to construct such a model capable of predicting all the possible diseases rather than a specific one. Generally, various machine and deep learning approaches are applied to different data sets of multiple diseases. However, sometimes, the model gets exhausted and fails to make accurate predictions because of noisy and distorted diagnostic images, even though ML and DL hold tremendous potential for assisting in GI diagnosis.

It is also observed that intelligent computing models limit their performances due to various factors such as the complexity of data and models, feature selection and extraction, Parameterization of the optimal model, time efficiency and scalability. The number of training and testing datasets is highly heterogeneous, and more high-quality datasets must be developed to develop intelligent models. In the future, these issues can be resolved by applying effective optimization techniques. These shortcomings must be carefully examined and addressed to ensure ML technologies' safe and effective introduction into clinical practice. The proper association between regulatory organizations, data scientists, and medical professionals is also required to overcome these challenges.

Conflict of Interest

The authors declare no conflict of interest.

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