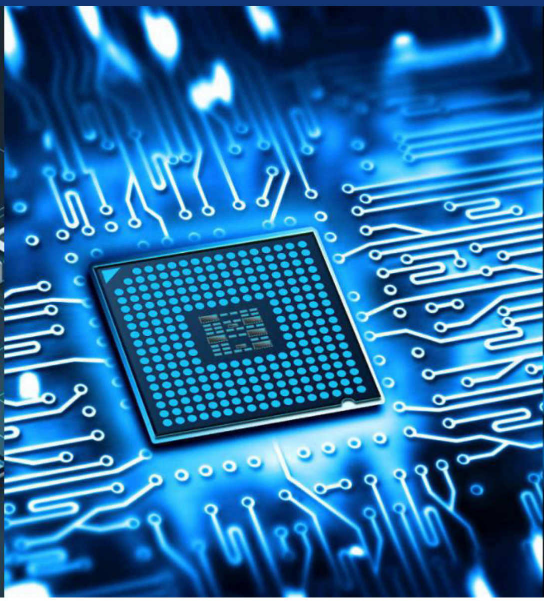
IJIRCCE

ISSN(O): 2320-9801

ISSN(P): 2320-9798



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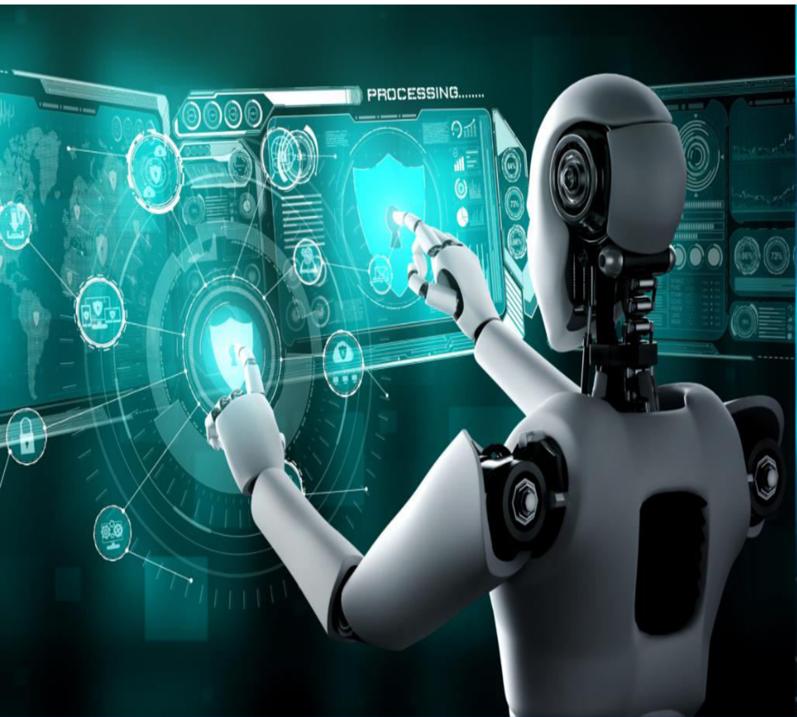

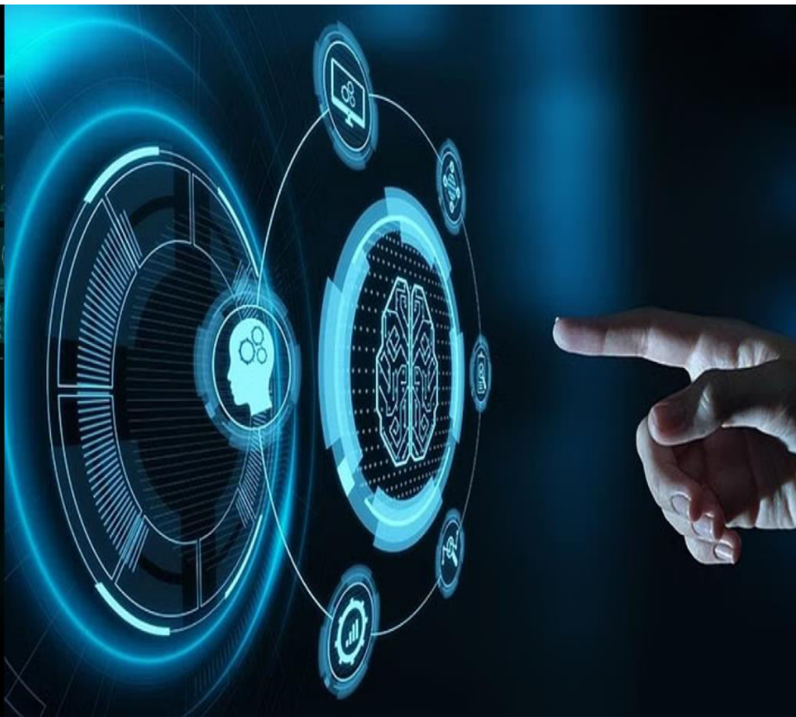

Impact Factor: 8.771

Volume 14, Issue 3, March 2026

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International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Empirical Study on Gastrointestinal Disease Diagnosis for Ulcer Detection with KVASIR Dataset

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ABSTRACT: Worldwide health concern has Gastrointestinal (GI) diseases that affect million people annually. GI diseases are ulcers in rigorous fitness complications when analyzed at earlier stage. At gastroenterology, Wireless capsule endoscopy (WCE) is utilized to examine GI area. WCE collects the images for performing GI disease diagnosis. Image pre-processing, feature extraction and classification are carried out for efficient GI disease diagnosis. The automated diagnosis systems collected the WCE images and find the GI disease in automatic way. The computer-aided algorithms extracted image features like texture, color, and shape for performing efficient image classification. But, traditional approaches failed to improve accuracy and lesser time. In order to address these issues, gastrointestinal illness analysis was carried out by employing ML as well as DL.

KEYWORDS: Gastrointestinal disease, diagnosis system, pre-processing, classification, gastroenterology, Wireless Capsule Endoscopy

I. PREAMBLE

Gastrointestinal sickness is maximum different population likelihood at significant frequency. In accordance with data released by World Health Organization (WHO), nearly 1.8 million people experienced challenges and caused gastrointestinal illnesses. GID diagnosis is the considered as an important field of research. (WCE) is an efficient diagnostic tool for performing the gastrointestinal (GI) tract disease diagnosis. At GI, Endoscopic image study has vital task.

The key objective of review article is given as:

- To perform efficient gastrointestinal disease diagnosis of endoscopic images with lesser time consumption and higher accuracy
- To discuss different GI disease diagnosis methods
- To compare conventional GI disease diagnosis performance for attaining enhanced results

Manuscript arranged by: review of gastrointestinal disease diagnosis methods discussed in Section 2. Section 3 and 4 describes of gastrointestinal disease diagnosis with endoscopic images. Factors as well as results presented in Section 5, 6. Conclusion and future work are shown in Section 7.

II. RELATED WORK

GI images are determined in [1] by Atrous Spatial Pyramid Pooling with Swin Transformer (ASPPST) approach. However, it failed to reduce complexity. Revolutionary Hexa categorization model was designed in [2] depending on Deep Hexa model for GT diseases in compressed WCE image.

In [3], with multiple operations like deep feature extraction from endoscopy images, pre-trained neural networks approach was designed. But, the image pre-processing time was not reduced. The robust deep network termed SNet was designed in [4] for addressing the classification issues with image resizing and feature extraction. But, the feature extraction accuracy was not improved by SNet.

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For GI discovery, groundbreaking ensemble method was introduced in [5]. However, the precision level was not improved by groundbreaking ensemble method. In [6], GI illness was established by Densely Connected Depth-wise Separable Convolution-Based Network (DCDS-Net) model. But, the error rate was not reduced by existing model.

Accuracy was enhanced [7] by Modified Salp Swarm Algorithm with Deep Learning based Gastrointestinal Tract Disease Classification (MSSADL-GITDC). However, it failed to categorize the disease with reduced time consumption. GI diseases classified [8] with Parallel Depthwise Separable Convolutional Neural Network and Pearson Correlation Coefficient and Ensemble Extreme Learning Machine (PD-CNN- PCC -EELM). But, it failed to increase the model efficiency.

An innovative deep learning approach was designed in [9] for efficient segmentation and classification of WCE images. GISegNet employed deep learning-based architecture for accurate gastrointestinal detection. To determine irregularity, computer-aided diagnostic (CAD) system was introduced [10].

WCE image was classified [11] during Squeeze-and-excitation (SE) + Residual Neural network (ResNet)-H GI lesion recognition. GI images identified [12] by snake optimization algorithm with DL-assisted GC classification (SOADL-GCC). Long-range transformer model was introduced in [13] with pixels and patches in architecture to transformer block.

Cancer was recognized [14] through GI Cancer Detection as well as Classification by African Vulture Optimization Algorithm and Transfer Learning (GICDC-AVOADL). A curriculum self-supervised learning framework was presented in [15] for human curriculum learning used HyperKvasir dataset for pre-training and fine-tuning.

Endoscopic images were examined [16] Endoscopic Image study for Gastrointestinal Tract Disease Diagnosis inspired Algorithm by Deep Learning (EIAGTD-NIADL). Magnifying endoscope system was introduced in [17] with endoscopic image enhancement technology to determine the technical feasibility for gastrointestinal tumor diagnosis.

A diffusion-based framework was introduced in [18] for image translation. CNN was introduced in [19] for early gastrointestinal disease diagnosis with high accuracy and robustness. The near-infrared fluorescence capsule endoscopy (NIFCE) was introduced in [20] to gather fluorescence images. NIFCE gathered white light (WL) images for identifying the lesions with morphological variations. In [21], Three-step method was introduced

A 13-layered (CNN) model termed GINet was introduced in [22] for efficient GI disease diagnosis, namely angiectasia, lymphangiectasia, GI bleeding, and ulcer. In [23], hierarchical Spatio Pyramid TranfoNet was introduced. STN improved the discriminative power between overlapping disease characteristics.

GI tract areas were introduced [24] via long-range transformer. A split token method was employed in transformer block to create local information. GI anomaly localization determined [25] during pointwise cross-feature-map descriptor. A vision Transformer model was introduced in [26] depending on shifted windows for image classification. Medical images investigated [27] with Hybrid Rice Optimization.

An innovative deep learning approach termed GISegNet was introduced in [28] for segmentation and classification of GI. Spatial-Attention ConvMixer (SAC) was introduced in [29] with patch extraction and spatial attention. SAM assigned the importance to every spatial location within feature maps. GI sickness was established [30] via DL.

III. DATASET DESCRIPTION

Dataset used is Hyper-Kvasir dataset obtained as of https://osf.io/mh9sj/. It includes GI tract images for ulcer discovery. It consists of 110,079 images as well as 373 videos attained through WCE. At this dataset, ulcer WCE images are gathered by whole of 851 obtainable.

IV. METHODOLOGY

In last 20 years, medical imaging knowledge is vital steps for routine disease analysis. To maintain good health, GI scheme has organs linked by food digestion. GI tract diseases comprise the major cause of mortality and morbidity on

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healthcare systems. Early detection and precise diagnosis plays an important role for patient risk prevention. In order to perform efficient GI tract screening, (WCE) is well-liked method used for performing the accurate detection among other medical images. The conventional deep learning methods are introduced for efficient GI tract disease prediction with WCE images. However, the prediction time was not minimized by existing methods. In order to address the existing methods, GI tract disease diagnosis is carried out in accurate manner.

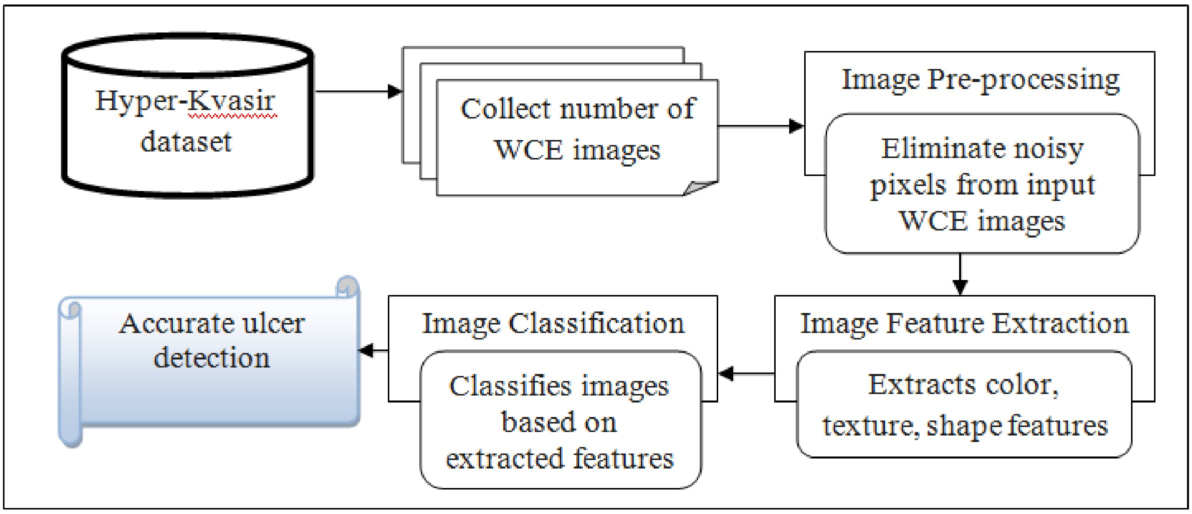

Figure 1 Architecture Diagram of Accurate Ulcer Detection

Architecture diagram of accurate ulcer detection are portrayed in Figure 1 with four fundamental processes.

4.1 Salp Swarm Algorithm by DL

The medical images are collected from the (WCE) for gastrointestinal disease diagnosis. Manual diagnosis is time consuming for medical practitioner. GIT sickness was detected in ML. Combine information growth as well as image processing techniques. By Endoscopic Images, MSSADL-GITDC was introduced. Image smoothening was carried out using median filtering (MF) method. Feature extracted by capsule network. Effectiveness enhanced with MSSA basis of hyperparameter tuning. For GIT, deep belief network was used. Backpropagation was employed for fine tuning of classification process.

4.2 DL with EELM and XAI

With minimum number of layers, PD-CNN was introduced to consider Pearson Correlation Coefficient. Diseases are recognized by EELM as well as L1 Regularized ELM. For improving image illustration, mixture preprocessing method was developed. Overhead was reduced on multiclass GI images. An interpretability as well as judgment making were increased with XAI as well as guided Saliency mapping. Practical intelligence introduced with higher confidence in GI disease diagnosis for real-world applications.

4.3 ASPPST method

GI lesions determination was essential one. Video categorization of GI endoscopic was demanding one. ASPPST classifies GI illness by endoscopic videos. The preprocessing algorithm was used to improve the GI frames. GI videos were determined to 30 dissimilar classes via superior CNN and Swin Transformer. Capability was developed by Grad-CAM. Designed approach employed AI for biomedical engineering applications.

4.4 DL based Duo-Feature Optimized Hexa-Classification

With different gastrointestinal disease recognition, revolutionary Hexa categorization model was introduced. Through wavelet-based Retinex as well as augmentation, input images gathered as of KVASIR and KID dataset. Preprocessing as well as feature extraction carried out. Shuffle network extract arithmetical features. Segmentation was

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executed in UNet. Walrus optimization selects optimal features via conditional entropy. Hexa classes discovered through capsule network to attain high GI disease detection accuracy.

4.5 Deep CNN

At medical, precise GIT classification was an essential demand. An image classification and detection was used in complicated system for efficient endoscopic image diagnosis and treatment. Multiple operations were considered by pre-trained neural networks. Binary dragonfly was employed through feature vectors. Three classes were recognized with Kvasir-V2 as well as COMSATS University Islamabad Wah private dataset.

4.6 CNN

A robust deep network termed SNet was introduced to provide the complex classification problems. An endoscopic image performed preprocessing subjected to feature extraction. Image pre-processing step performed. In diverse layers, CNN used six blocks positioned.CNN model performed efficient training with HyperKvasir dataset. Curse of dimensionality problems were handled by lowest redundancy highest relevance method through applicable feature selection.

4.7 Deep CNN Model with Beta Normalization Aggregation

To achieve GI discovery, ensemble method was introduced. The designed method accelerated the training and enhanced capacity to distinguish the diverse patterns with gastrointestinal conditions. The designed method employed beta normalization aggregation consistent. Precision was improved via refined aggregation. Designed method outperformed individual base model for efficient gastrointestinal diagnosis. Decision making process was carried out with improved interpretability and trustworthiness. Novel weighted average as well as better beta normalization was introduced with maximum accuracy.

4.8 Deep Transfer Network based Depth-Wise Separable Convolution

Endoscopic GI illness identified by DCDS-Net. At DCB, global average pooling, batch normalization, dropout as well as dense layers were employed. DCDS-Net model enhanced gastrointestinal diagnosis performance. Transfer learning employed to minimize the overfitting problems and to determine optimal fine-tuning. Data augmentation was integrated into pipeline for increasing the gastrointestinal diagnosis performance. Grad-CAM was employed to create heatmaps to recognize GI tract regions for identifying the disease presence.

4.9 Optimal CapsNet Model based Computer Aided Diagnosis

To categorize GI, SOADL-GCC was introduced. With maximum image quality, BF employed. CapsNet extracts essential feature vectors. Classification was performed by DBN. Discovery outcomes were enhanced by Kvasir dataset. SOADL-GCC technique increased the classification accuracy.

V. EXPERIMENTAL METRICS

Four different performance metrics employed for performing efficient gastrointestinal tract disease diagnosis with several metrics. Percentage of WCE images properly determined as ulcers is defined as Ulcer detection accuracy (UDA). 'TR_p' denote the true positives that the images are correctly detected as ulcer, 'TR_n' symbolizes true negative refers to correctly predicted normal images as normal. 'FL_p' as well as 'FL_N' denote false positive and negative. The accuracy is measured in percentage (%). Relation of 'TR_p' properly is identified ulcer images as ulcers is measured as Precision (Pre). Recall (Rcl) computed as relation of 'TR_p' identified ulcer images.

Time needed to find ulcer is estimated as Ulcer detection time (UDT). '$Tme\ [UD]$' is time for discovery of single image 'EI_i'. Table 2 shows metrics for gastrointestinal tract disease diagnosis.

© 2026 IJIRCCE | Volume 14, Issue 3, March 2026| DOI:10.15680/IJIRCCE.2026.1403025

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Table 2 Performance Metrics

Parameter	Formula
UDA	$\left(\frac{TR_p + TR_n}{TR_p + TR_n + FL_p + FL_n}\right) * 100$
Pre	$\frac{TR_p}{TR_p + FL_p} * 100$
Rcl	$\frac{TR_p}{TR_p + FL_n} * 100$
UDT	$\sum_{i=1}^{n} EI_i * Tme \ [UD]$

VI. RESULT AND DISCUSSION

The performance result analysis based on efficient gastrointestinal tract disease diagnosis, namely ulcer detection. The performance evaluation is different evaluation metrics to determine the efficiency of gastrointestinal tract disease diagnosis.

Table 3 Tabulation for Experimental Results of KVASIR Dataset

Methods/Parameters	Ulcer Detection Accuracy (%)	Precision (%)	Recall (%)	Ulcer Detection Time (ms)
MSSADL-GITDC approach	91.2	92.8	93.4	25
PD-CNN-PCC-EELM	89.3	90.5	91.2	28
ASPPST method	88.5	89.9	90.5	31
Revolutionary Hexa categorization model	87.3	88.5	89.6	33
Pre-trained neural networks	89.9	90.1	91.8	29
SNet	90.5	91.4	92.5	27
Groundbreaking ensemble method	88.6	89.4	90.2	30
DCDS-Net model	89.4	90.5	91.4	27
SOADL-GCC technique	90.8	91.2	92.3	26

Performance outcome with nine techniques are illustrated for KVASIR dataset in Table 3. MSSADL-GITDC approach achieved better gastrointestinal tract disease diagnosis results than any other conventional methods. For KVASIR dataset, MSSADL-GITDC approach attained 91.2% of ulcer detection accuracy, 92.8% of precision,93.4% of recall and25ms of ulcer detection time. Figure 2 illustrates the performance metric analysis of KVASIR dataset.

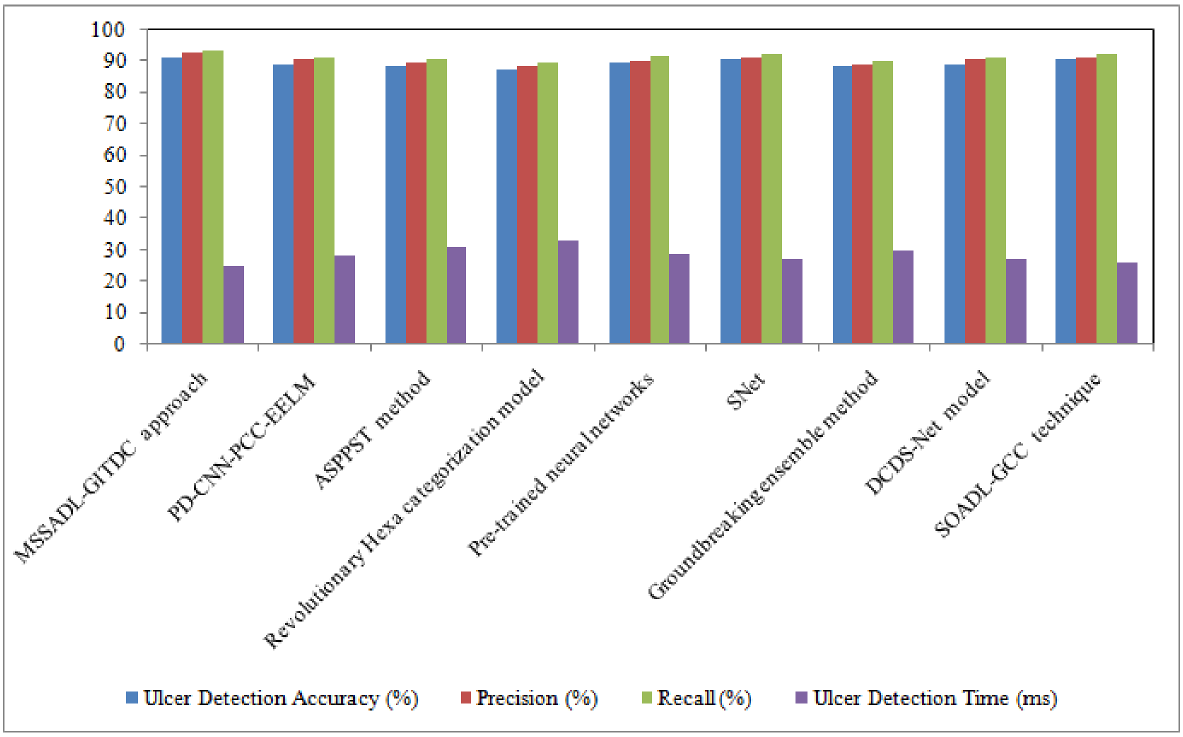

Figure 2 Performance Analysis on KVASIR dataset

Figure 2, MSSADL-GITDC method using KVASIR dataset increases ulcer detection accuracy by 2%, precision by 3%, recall by 2% and reduced ulcer detection time by 13% when compared to existing ulcer detection techniques.

VII. CONCLUSION

In this work, MSSADL-GITDC approach attained higher accuracy during gastrointestinal tract disease diagnosis. MSSADL-GITDC approach achieves highest precision and lesser time consumption during ulcer detection than all the other existing techniques. Different performance parameters are used to examine the gastrointestinal tract disease diagnosis performance results. In future, ML as well as DL will be employed to efficient ulcer detection instead of the other conventional ulcer recognition methods.

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