International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-07, Issue-10, JAN 2022

U-Net model for efficient bleeding detection in wireless capsule endoscopy images

Diffia W, Master of Engineering in communication systems in Arunachala college of engineering for women Vellichanthai, India.

Y.P.Arul Teen, Assistant Professor, Department of Electronics and Communication Engineering, University college of Engineering Nagercoil, India.

Abstract: **Ulcers and bleeding are frequent signs of more serious small intestinal illnesses. In most cases, ulcers and bleeding in the small intestine are asymptomatic. Only early detection of this can potentially save many human lives from the most lethal diseases. Wireless capsule endoscopy (WCE) is being used to make early diagnoses of small intestinal disorders. Simultaneously, it is a difficult and time-consuming task for a clinician to accurately diagnose bleeding and ulcers using wireless capsule endoscopy images. As a result, building an automated computer-aided ulcer and bleeding detection system is a critical area of research. A fully automated ulcer and bleeding detection system is built in this suggested method employing a redesigned U-Net (MU-Net). The proposed U-Net-based bleeding detection system is compared to previously developed CNN-based bleeding detection methods. The study's findings demonstrate that the suggested U-Net-based bleeding detection system is both accurate and fast.**

Keywords —CNN, Deep Learning, Image processing, Machine Learning, Stomach Bleeding Detection.

I. INTRODUCTION

Acute gastrointestinal (GI) bleeding, often known as blood loss, can occur anywhere throughout the digestive tract from the mouth to the anus [16]. Bleeding can be severe for a short period of time or extremely modest for a long period of time, and it can remain for several years. Upper gastrointestinal bleeding and lower gastrointestinal bleeding are the two most common classifications for gastrointestinal bleeding [17]. Upper gastrointestinal bleeding, dark red vomiting, and vomit that looks like ground coffee, dark stools, or bloody stools are all possible symptoms. Dark red stools with painful are signs of lower gastrointestinal bleeding [18].

Chronic blood loss is connected with pale complexion, anaemia, cardiac issues, starvation, and lethargy. Due to the life-threatening nature of any sort of blood loss, gastrointestinal bleeding should be detected and treated promptly. Cancer of the gastrointestinal system is one of the most deadly diseases that can affect a person at any age. Stomach and small intestine cancers are the fourth major cause of mortality from cancer in India. Early recognition of the disease's first signs, such as ulcers and bleeding, can easily safeguard people from the most dangerous aspects of the condition. Traditional endoscopic procedures for patients with ulcers and bleeding are a risky and painful medical procedure [19]. Additionally, this method has a number of limits and disadvantages. As a result, detecting effective bleeding and ulcers with standard endoscopy is quite challenging.

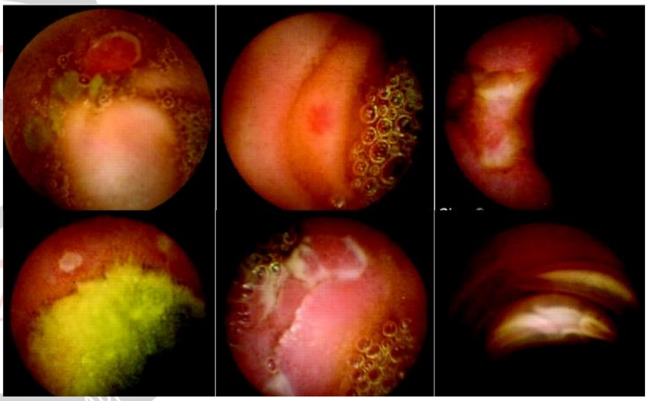

Fig1 Sample images of gastric bleedings.

Wireless capsule endoscopy is a significant advancement in medical science [20]. They attach the camera, which is in the form of a little tablet, and then send it into the food zone to capture images. This camera determines the location of the disease. It's simple to diagnose using this camera, which can take up to 50,000 images in eight hours. It assists patients in initiating treatment more quickly. On the other hand, it is quite difficult for a physician to quickly and accurately identify the abnormalities in the images captured during this Wireless Capsule Endoscopy process. The purpose of this article is to build an efficient computer-aided bleeding detection technique utilizing U-Net.

The U-Net architecture is the most often utilized convolutional neural network architecture for image segmentation [21][22]. Due to its U-shaped design, it is called U-Net. Its architecture is composed on three modules: contracting, bottlenecking, and expanding or up sampling.

 DOI : 10.35291/2454-9150.2022.0036

The purpose of this suggested research is to apply the skip connection idea to increase the accuracy and speed of traditional U-Net for detecting bleeding region in WCE images.

The remainder of the paper is structured as follows: The literature review is detailed in Section II, and the proposed U-Net for WCE image bleeding detection is detailed in Section III. Finally, Section IV discusses the results, and Section V presents concluding remarks.

II. Literature Review

Numerous automatic detection and recognition systems have been created by researchers. These are primarily supervised learning algorithms that employ handcrafted and CNN features for the detection and recognition of digestive diseases. An approach for detecting stomach cancer is provided that is based on Gabor features and a Faster Region-Based CNN (Faster R-CNN). Combining handcrafted Gabor features with CNN descriptors was used in this strategy [1]. When paired with CNN features, Gabor features become more successful [2], and numerous studies have demonstrated the usefulness of combining handcrafted Gabor and deep features [3]–[4]. A CNN-based model for the detection of ulcer, polyp, and erosion is constructed. For the detection of stomach infections, CNN features are combined with SVM. This approach achieved a 93 percent accuracy rate [5]. This system made use of SqueezNet's fire segments. This strategy decreases the size of the network and obtains a 92.90 percent accuracy. Billah et al. [6] blend color wavelet and convolutional neural network characteristics. SVM is utilized to obtain the results during the classification phase. Geometric features extracted from segmented regions of GI pictures are used in. The geometric traits are then integrated with the VGG-19 and VGG-16 features. The Euclidean Fisher Vector technique is used to combine the deep characteristics of VGG-19 and VGG-16.

[7] describes a strategy based on color transformations. On RGB images, the HSI and YIQ transformations are applied to determine the maximum and minimum pixel values. After extracting and fusing Local Binary Pattern (LBP) and Gary Level Co-occurrences Matrices (GLCM) features with color-based data, the final vector is given to the multi-layer perceptron. This approach is used to identify and classify stomach illnesses. A model for ulcer identification based on YIQ colour transformation is proposed [8]. This approach makes use of the Y plane, whereas the classification phase makes use of SVM. Suman et al. developed a technique based on statistical colour features for the automated diagnosis of stomach bleeding.

For automatic ulcer detection, a two-phase approach is developed [9]. The initial step is to detect the contaminated region using a super pixels-based saliency approach. The second phase introduces the saliency-based maximum pooling (SMP) approach. The SMP approach is then combined with locality restricted linear coding (LLC) to achieve the classification accuracy of 93.65 percent.

A method for classifying ulcers and non-ulcers based on textural traits was devised. The resulting feature vector was then fed into the SVM classifier, which attained an accuracy of 94.90 percent [10]. Fan et al. [11] developed a system for recognizing stomach disorders using LBP and Scale-Invariant Feature Transform (SIFT) features. SVM is used to extract and classify characteristics such as the discrete wavelet transform (DWT), variance, and LBP for the detection of colon infections. Texture information is derived from these characteristics, and classification results are obtained using an SVM classifier [13]. The Bag of Visual Words (BoW) is constructed using features derived from several color spaces and color histograms for the purpose of detecting bleeding [15]. They extract and merge features from pre-trained networks such as Inception-V3 and VGGNet.

III. Proposed Method

As illustrated in Figure 2, the framework for detecting and segmenting WCE bleeding comprises of a data pre-processing module, a U-net training method, and a testing procedure. The border and corner zones of WCE images are eliminated during data pre-processing. The U-net is then trained using the pre-processed training data. Following the same pre-processing processes as in the training approach, the testing data is fed into the trained U-net to obtain the segmentation results.

A. Image pre-Processing

Due to an inherent circular aperture in front of the WCE camera inside the small intestine, the center region (circular or semi-octagonal) of WCE image contains essential information. The pixels surrounding the center region have a comparatively low intensity. The suggested pre-processing step eliminates black pixels from the border and corner zones of WCE pictures, taking into consideration the region's pixel intensity variance and circular form.

B. Image augmentation

Only when there is sufficient training data can the deep neural network perform effectively. Enhancement of images is critical for achieving a better outcome with a little training data set. The use of image augmentation simplifies the training procedure and increases classifier accuracy. Artificial image augmentation is accomplished using a range of image processing techniques, including flips, shifters, and random rotation. In this study, the WCE image is enhanced by rotating it 90,180,270 degrees and flipping it.

 DOI : 10.35291/2454-9150.2022.0036

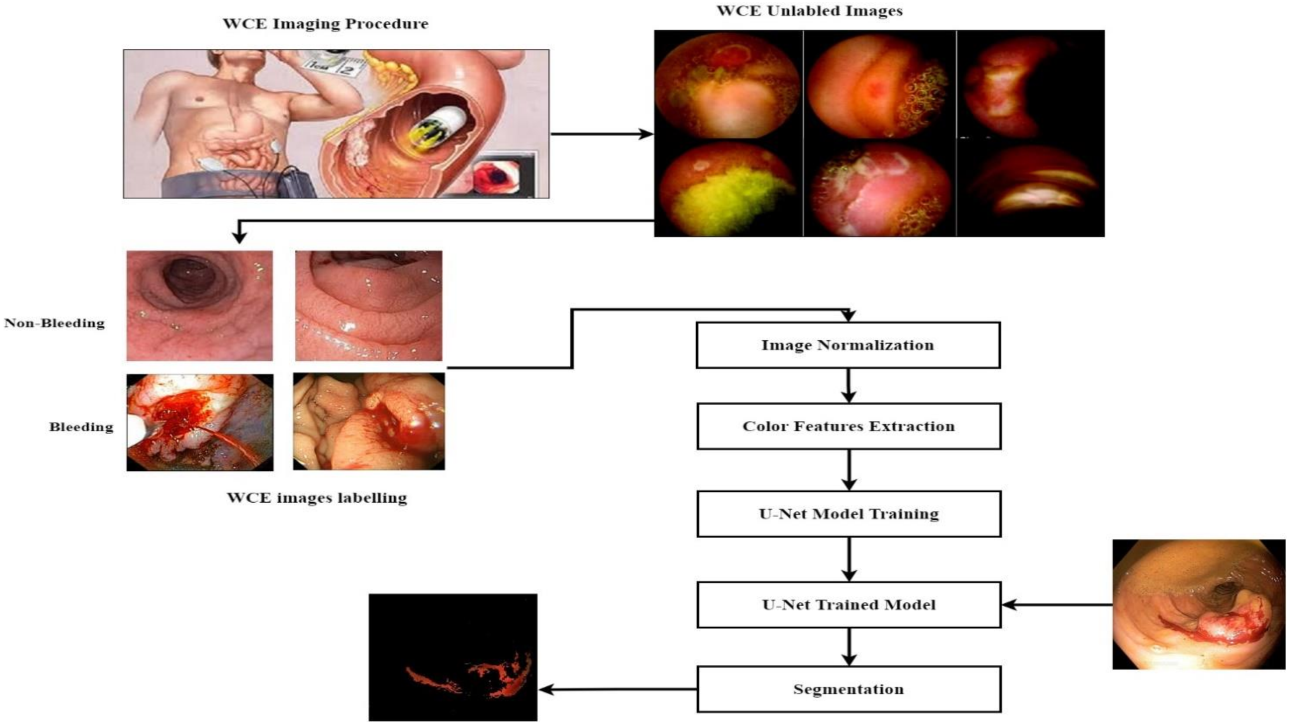

Fig 2: the WCE image bleeding detection system's proposed architecture.

C. Color Feature Extraction

Feature extraction is a critical component of classification algorithms. The suggested study extracts various color elements from pre-processed WCE images. With color feature extraction, it is simple to determine whether or not there have been any color changes in the WCE images. This proposed method employs the feature selection method to extract the most optimal color features from WCE images. This exceptional color features considerably improve prediction accuracy while lowering the computing cost associated with training deep learning models.

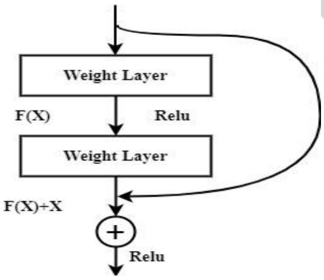

Fig 3: Residual learning model for U-Net.

D. proposed U-Net architecture

In this proposed U-Net architecture, Residual-Based Learning (RBL) is used to increase learning efficiency. The Residual block's architecture is depicted in Figure 3.

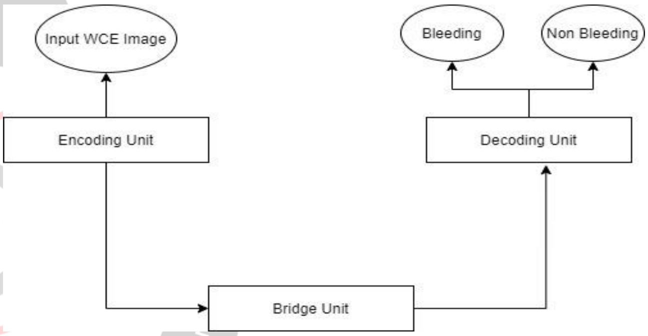

Fig 4: The suggested automatic U-Net-based bleeding segmentation algorithm's workflow.

The shortcut connection implements the Residual block. The shortcut adds the block's input and output element by element. This simple modification will not only add additional parameters and calculations to the network, but it will also significantly raise the model's training speed and effectiveness. In the above architecture, X denotes the input image of a bleeding and $F(X)$ denotes the activation function. The proposed U-Net architecture is divided into three modules: encoding, decoding and bridge.

Pre-processed and augmented images are obtained as input through the encoding layer. High level and low level color features are extracted from these input images. The High Correlated Feature Learning method determines the relationship between a bleeding's class label and feature vectors. From there, high level and low level features with positive values are selected. Then it is given as input to the bridge layer. The encoding and decoding modules are connected through the bridge module. The bridge module has two normalization units, two ReLU units, two convolutional units and a concatenation unit. The decoding

 DOI : 10.35291/2454-9150.2022.0036

unit classifies the highly correlated texture properties of the WCE bleeding region is extracted by the encoding unit. During the network training phase use binary cross entropy as a loss function, and the network output of the last layer is $O_i \in [0,1], and\ y_i \in \{0,1\}$ representing the genuine segmentation result. The loss function was created as follows:

$$L = \sum_i y_i \log o_i + (1 - y_i) \log(1 - o_i) \qquad (1)$$

IV Results and Discussion

A. Hardware Configuration

In this research, the computer configuration used to execute the software is as follows: GPU: NVIDIA GeForce GTX 960; CPU: Intel(R) Core(TM) i5-4660 3.20 GHz. The operating system is Windows 10, and the software configuration includes Matlab and image processing packages.

B. Dataset Details

To evaluate the presented method's effectiveness, numerous WCE images are acquired from a frequently used publically available database. The database provides the ground truth labelling of bleeding and non-bleeding images. The simulation results are presented on 420 WCE images, 220 of which are categorized as bleeding and 200 as non-bleeding. A skilled physician manually comments on bleeding photos, and if bleeding, curves out the bleeding zones.

The proposed U-Net-based approach for bleeding region segmentation in WCE images is compared to existing deep learning-based systems using the most important accuracy measures, including Total Accuracy (TA), Precession (PRE), Recall (REC), and F1-Measure (F1-M). Each of these performance indicators varies according to the following accuracy variables. True Positive WCE images bleeding region segmentation, True Negative WCE images bleeding region segmentation, False Positive WCE images bleeding region segmentation and False Negative WCE images bleeding region segmentation.

True Positive WCE images bleeding region segmentation: If the proposed approach accurately detects the bleeding region from inner GI tract images with complicated color and dark background, it is referred to as true positive WCE images bleeding region segmentation. The variable TP determines this.

True Negative WCE images bleeding region segmentation: If the proposed approach correctly identifies non bleeding region from WCE images with complicated color and dark background, it is referred to as true negative WCE images bleeding region segmentation. The variable TN determines this.

False Positive WCE images bleeding region segmentation: If the proposed approach fails to correctly identify bleeding regions due to complex color and dark background of GI tract, it is referred to as False Positive WCE images bleeding region segmentation. The variable FP determines this.

False Positive WCE images bleeding region segmentation: If the suggested technique fails to correctly identify non bleeding regions due to intricate color and darken background, it is referred to as False Negative WCE images bleeding region segmentation. The variable FN determines this.

Equation 2 determines the total accuracy (TA) of the proposed U-Net prediction models.

$$TA = \frac{TP+TN}{TTP+TN+FP+FN} \quad (2)$$

The suggested U-Net prediction models' precession rate (PRE) is determined by equation 3.

$$PRE = \frac{TP}{TP+FP} \quad (3)$$

The proposed U-Net prediction models' recall rate (REC) is calculated by equation 4.

$$REC = \frac{TP}{TP+FN} \quad (4)$$

The F1- Measure (F1) of the proposed U-Net prediction models is determined by the equation 5.

$$F1 = \frac{2(PRE \times REC)}{\text{PRE+REC}} \quad (5)$$

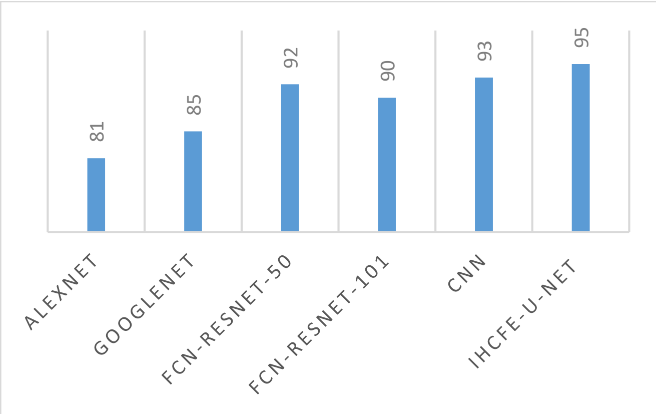

Fig 5. Total accuracy comparison of proposed U-Net -based approach for WCE images bleeding region segmentation system and existing methods.

DOI : 10.35291/2454-9150.2022.0036

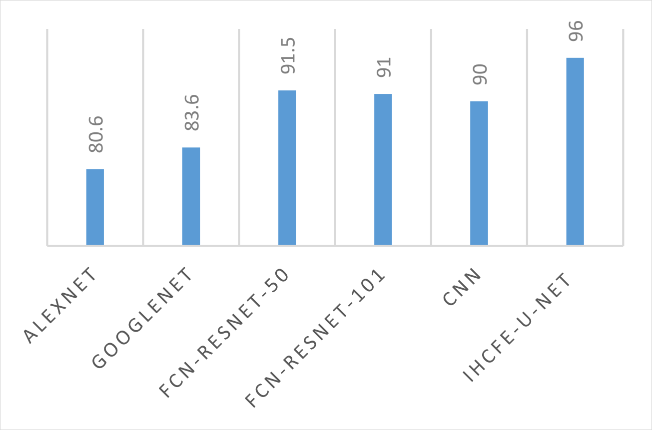

Fig 6 Precession rate comparison of proposed U-Net -based approach for WCE images bleeding region segmentation system and existing methods.

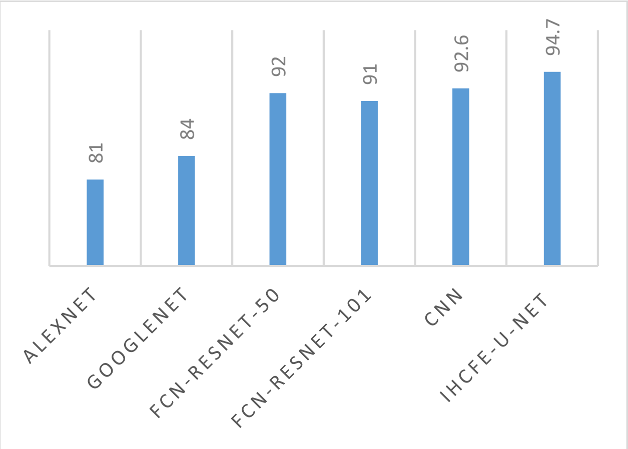

Fig 7. Recall rate comparison of proposed U-Net -based approach for WCE images bleeding region segmentation system with existing methods.

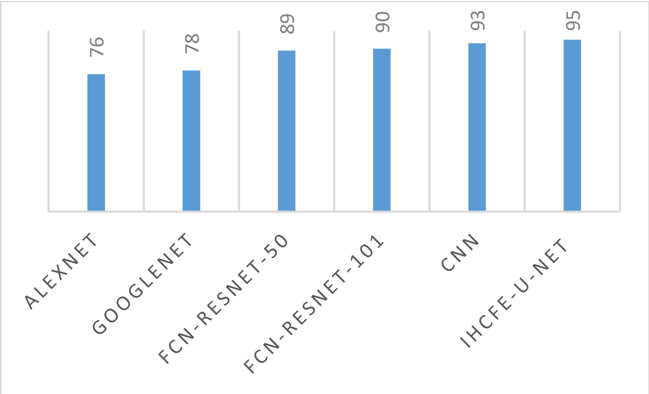

Fig 8. F1-messoure comparison of U-Net -based approach for WCE images bleeding region segmentation system with existing methods.

To demonstrate the proposed U-Net-based approach's prediction accuracy for WCE bleeding region categorization, the proposed and existing approaches were experimentally compared. Figure 5 depicts the comparing results visually. The proposed approach extracts highly correlated color features, which are then fed into the U-Net model. The proposed WCE images bleeding region segmentation system has the best accuracy ratio of 95%. The primary reason for this is because the appropriate feature extraction method is applied. The experimental results reveal that the proposed method's FP rate has dropped. As a result, precession and accuracy are improved. Figure 6 depicts the precession variations of the proposed method versus existing methods. The proposed approaches achieve a maximum prediction accuracy of 96%. The enhanced U-Net model significantly reduces the FN rate, resulting in considerable increases in the proposed method's total accuracy and recall. Figure 7 depicts the recall comparison findings of the proposed and existing deep learning approaches. The proposed method achieves a maximum prediction rate of 94%. This study's f1-Messure is actually quite high because the f1-Messure is calculated using precession and recall. Figure 8 clearly shows the f1-Messure comparative results. The proposed technique achieves 93 % of the highest f1-message.

V CONCLUSION

Wireless Capsule Endoscopy is a breakthrough in medical science. This allows for early detection of a variety of diseases of the gastrological tract. In this proposed research, the modified U-Net concept is implemented and thereby bleeding segmentation is performed. Skip connection is invoked here to improve the performance of U-Net architecture. Thus the complicated structure of network architecture is modified. Also the accuracy and speed of bleeding segmentation has been greatly improved. The experimental results make it clear.

References

[1] N. Ghatwary, X. Ye, and M. Zolgharni, ‘‘Esophageal abnormality detection using DenseNet based faster R-CNN with Gabor features,’’ IEEE Access, vol. 7, pp. 84374–84385, 2019.

[2] Q. Shi, W. Li, F. Zhang, W. Hu, X. Sun, and L. Gao, ‘‘Deep CNN with multi-scale rotation invariance features for ship classification,’’ IEEE Access, vol. 6, pp. 38656–38668, 2018.

[3] S. Luan, C. Chen, B. Zhang, J. Han, and J. Liu, ‘‘Gabor convolutional networks,’’ IEEE Trans. Image Process., vol. 27, no. 9, pp. 4357–4366, Sep. 2018.

[4] H. Yao, L. Chuyi, H. Dan, and Y. Weiyu, ‘‘Gabor feature based convolutional neural network for object recognition in natural scene,’’ in Proc. 3rd Int. Conf. Inf. Sci. Control Eng. (ICISCE), Jul. 2016, pp. 386–390.

[5] Kwolek, ‘‘Face detection using convolutional neural networks and Gabor filters,’’ in Proc. Int. Conf. Artif. Neural Netw., 2005, pp. 551–556.

[6] Y. Chen, L. Zhu, P. Ghamisi, X. Jia, G. Li, and L. Tang, ‘‘Hyperspectral images classification with Gabor filtering and convolutional neural network,’’ IEEE Geosci. Remote Sens. Lett., vol. 14, no. 12, pp. 2355–2359, Dec. 2017.

[7] X. Zhang, W. Hu, F. Chen, J. Liu, Y. Yang, L. Wang, H. Duan, and J. Si, ‘‘Gastric precancerous diseases

 DOI : 10.35291/2454-9150.2022.0036

classification using CNN with a concise model,'' PLoS ONE, vol. 12, no. 9, Sep. 2017, Art. no. e0185508.

[8] M. Billah, S. Waheed, and M. M. Rahman, ''An automatic gastrointestinal polyp detection system in video endoscopy using fusion of color wavelet and convolutional neural network features,'' Int. J. Biomed. Imag., vol. 2017, pp. 1–9, Aug. 2017.

[9] M. A. Khan, M. Rashid, M. Sharif, K. Javed, and T. Akram, ''Classification of gastrointestinal diseases of stomach from WCE using improved saliency-based method and discriminant features selection,'' Multimedia Tools Appl., vol. 78, pp. 27743–27770, Jun. 2019.

[10] Y. Yuan, J. Wang, B. Li, and M. Q.-H. Meng, ''Saliency based ulcer detection for wireless capsule endoscopy diagnosis,'' IEEE Trans. Med. Imag., vol. 34, no. 10, pp. 2046–2057, Oct. 2015.

[11] S. Charfi and M. E. Ansari, ''Computer-aided diagnosis system for colon abnormalities detection in wireless capsule endoscopy images,'' Multimedia Tools Appl., vol. 77, no. 3, pp. 4047–4064, Feb. 2018.

[12] Y. Yuan, B. Li, and M. Q.-H. Meng, ''Bleeding frame and region detection in the wireless capsule endoscopy video,'' IEEE J. Biomed. Health Informat., vol. 20, no. 2, pp. 624–630, Mar. 2016.

[13] T. Agrawal, R. Gupta, S. Sahu, and C. Y. Espy-Wilson, ''SCL-UMD at the medico task-MediaEval 2017: Transfer learning based classification of medical images,'' in MediaEval, 2017.

[14] K. Pogorelov, K. R.Randel, C. Griwodz, S. L. Eskeland, T. de Lange, D. Johansen, C. Spampinato, D. T. Dang-Nguyen, M. Lux, P. T. Schmidt, and M. Riegler, ''Kvasir: A multi-class image dataset for computer aided gastrointestinal disease detection,'' in Proc. 8th ACM Multimedia Syst. Conf., Jun. 2017, pp. 164–169.

[15] J. C. Barbosa, J. Ramos, J. H. Correia, and C. S. Lima, ''Automatic detection of small bowel tumors in capsule endoscopy based on color curvelet covariance statistical texture descriptors,'' in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Sep. 2009, pp. 6683–6686.

[16] Cabrera D., White A. (2020) Management of Gastrointestinal Bleeding. In: Mookherjee S., Beste L.A., Klein J.W., Wright J. (eds) Chalk Talks in Internal Medicine. Springer, Cham. https://doi.org/10.1007/978-3-030-34814-4_16.

[17] Banerjee R., Reddy D.N. (2020) Upper Gastrointestinal Bleeding. In: Chawla R., Todi S. (eds) ICU Protocols. Springer, Singapore. https://doi.org/10.1007/978-981-15-0898-1_37.

[18] Gama-Rodrigues J., Proscurshim I., Jacob C.E. (2009) Upper Gastrointestinal Hemorrhage: Diagnosis and Treatment. In: Bland K.I., Büchler M.W., Csendes A., Sarr M.G., Garden O.J., Wong J. (eds) General Surgery. Springer, London. https://doi.org/10.1007/978-1-84628-833-3_128.

[19] Yao, K., Doyama, H., Gotoda, T. et al. Diagnostic performance and limitations of magnifying narrow-band imaging in screening endoscopy of early gastric cancer: a prospective multicenter feasibility study. Gastric Cancer 17, 669–679 (2014). https://doi.org/10.1007/s10120-013-0332-0.

[20] Nakamura, T., Terano, A. Capsule endoscopy: past, present, and future. J Gastroenterol 43, 93–99 (2008). https://doi.org/10.1007/s00535-007-2153-6.

[21] Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab N., Hornegger J., Wells W., Frangi A. (eds) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015. Lecture Notes in Computer Science, vol 9351. Springer, Cham. https://doi.org/10.1007/978-3-319-24574-4_28.

[22] Kumthekar, A., Reddy, G.R. An integrated deep learning framework of U-Net and inception module for cloud detection of remote sensing images. Arab J Geosci 14, 1900 (2021). https://doi.org/10.1007/s12517-021-08259-w.

 DOI : 10.35291/2454-9150.2022.0036