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Fractional Stochastic Gradient Descent Trained SM-Segnet-Based Segmentation And Capsule Neural Network For Colon Cancer Detection

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Abstract

Cancer that forms in the epithelial cells of the large intestine which then proliferate to the neighboring regions is called colon cancer. Early diagnosis is vital for efficient treatment and for the recovery from this disease. Detection of colon cancer at the preliminary stages can significantly assist physicians in decision-making and thus decrease the hardships. Accurate detection of colon cancer could be attained by automatic models that process the medical image to detect cancerous growth. The prevailing techniques developed for colon cancer detection that depend on Deep Learning (DL) models necessities more computational ability as well as resources. This paper proposes a novel segmentation technique that uses the Fractional Stochastic Gradient Descent (FSGD) to train the Squeeze M-SegNet (SM-SegNet). The SM-SegNet is utilized for segmenting the required region of the colonoscopy image that is preprocessed by the Non-Local Means (NLM) filter for noise removal. Finally, the Capsule Neural Network (CapsNet) is used for detecting colon cancer. The developed methodology is analyzed by considering metrics like specificity, sensitivity, and accuracy. The experimental result illustrates that the developed method recorded an accuracy of 0.918 which is comparably superior to the prevailing systems, and sensitivity and specificity recorded are 0.907 and 0.927 respectively.

Keywords: Colon cancer, Squeeze M-SegNet, Capsule Neural Network, Non-Local Means filter, Fractional Stochastic Gradient Descent.

1. Introduction

Cancer is a commonly found disease in which the abnormal cell starts to grow in unrestricted mode in any organ or tissue. It is the second top reason for death globally, regarding for almost 9.6 million deaths [8]. A kind of cancer called Adenocarcinomas harm the linings of the large intestine (colon) as well as the rectum, causing malignancy in the large intestine and rectum. A growth appearing like a button on the outer layer of the rectum or intestine is colorectal cancer which is otherwise called colon cancer. If the Intestine or the rectum is affected, it might occupy the neighboring lymph nodes. As the blood usually flows from the wall of the intestine or rectum into the liver, colon cancer can penetrate to liver after proliferating to the neighboring lumps [4]. Colon cancer affects people of all ages but is commonly found in senior citizens around 50-60 years. Two distinct forms of adenocarcinomas are Mucinous adenocarcinomas and signet ring cell adenocarcinomas [1]. The risk of colon cancer increases due to diet factors along with family history. Family history, such as hereditary disease in the intestine and the food which are high in fat and low in fiber enhances the danger of colon cancer. Fatigue, weakness and blood in feces are some of the major symptoms of colon cancer [4]. An ideal way of preventing this type of cancer is the endoscopic elimination of pre cancerous sore. The effective therapy of colon cancer requires an accurate, early, and reliable endoscopic diagnosis [10].

A prime testing method for detecting colon cancer is colonoscopy. It also posses the ability to prevent of colon cancer by eradicating pre cancerous sores and hence was an important tool for enhancing medical diagnosis. Regrettably, it does not produce 100% accuracy and even the persons tested negative are found to develop cancer months or years later on. Hence, enhancing the rate of detection is essential [9]. Existing methods for colon cancer are tedious and time consuming [1]. However, the technological progressions in medical image and image processing area have offered various computer-aided diagnostics methods [6]. Human assessment of the medical images by specialists is challenging and insubstantial. Furthermore, the early stage symptoms are very vague and early detection of colon cancer is actually complex and symptoms turn out to be apparent only on the severe stages [9]. Lately, the automated colon cancer detection system based on Computer-Assisted Diagnosis (CAD) namely Machine Learning (ML) and Deep Learning (DL) [7]. However, the cancer detection systems based on ML need manual extraction of features [4], whereas, DL methods are highly efficient in automated cancer detection [4]. Recently, medical image processing using Deep Neural Networks (DNNs), that merges classification as well as feature extraction within a unified learning structure came to existence [6]. The standard deep structures that are based on Convolutional Neural Network (CNN) have been broadly utilized for segmentation and classification of colon lesions [10]. Thus difficult as well as complex data can be interpreted effectively using both pre-designed and pre-trained CNN [7].

This paper develops a method for efficiently detecting colon cancer. It employs a Non-local Means (NLM) filter for preprocessing the input image and Squeeze M-SegNet (SM-SegNet) for segmenting the preprocessed image. The SM-SegNet is trained by the proposed Fractional Stochastic Gradient Descent (FSGD) that is obtained by merging Fractional Calculus (FC) with Stochastic Gradient Descent (SGD) algorithm. Lastly, the presence of colon cancer is detected by the Capsule Neural Network (CapsNet).

Major contribution of the work developed for colon cancer detection is described as follows

- ***Proposed FSGD SM-SegNet for colon cancer detection:*** A novel segmentation technique FSGD was developed for training the SM-SegNet for segmenting the colon images efficiently. The introduced FSGD is obtained via merging the FC with SGD.

The organization of the enduring part of this paper is stated beneath: part 2 describes the different technique that exist for colon cancer detection. part 3 explains the presented work, part 4 portrays the outcomes and assessment of the presented work, and finally the part 5, deliberates the conclusion.

2. Motivation

The prevailing techniques for colon cancer detection are assessed and the difficulties endured by them are discussed. The early symptoms for colon cancer are very vague and highly difficult to detect. In addition, it is hard to interpret the progression of colon cancer cells. Overcoming these hardships faced by the prevailing methods was the chief motivation for the proposed FSGD trained SM-SegNet.

2.1. Literature Review

Among many established techniques for colon cancer four methods are described briefly with their pros and cons. Hasan, I., *et al.* [1] implemented a Deep Convolutional Neural Network (DCNN) for colon cancer detection. This method was an automated and reliable system with fewer layers and resulted in shorter execution time. But its performance was relatively lower, and it was trained on small dataset hence it was less stable. Gerwert, K.,*et al.*[2] proposed CNN with Visual Geometry Group (CNN-VGGNet) for early detection of colon cancer, and it exhibited high training stability and produced superior results even with the limited patients. However, it was not applied for real time scenarios. Mohamed, A.A.A., *et al.* [3] devised the CNN based on SqueezeNet and Grasshopper Optimization Algorithm (GOA) for detecting colon cancer. The devised model had less computations and had a very low error rate, yet it faced the overfitting problem. Ho, C., *et al.* [5] proposed the Faster Region Based CNN (Faster-RCNN) for colorectal cancer screening. This method avoided the overfitting problem and minimized the false negative ratio. However, this method had high computational complexity and showed more misclassification.

2.2. Challenges

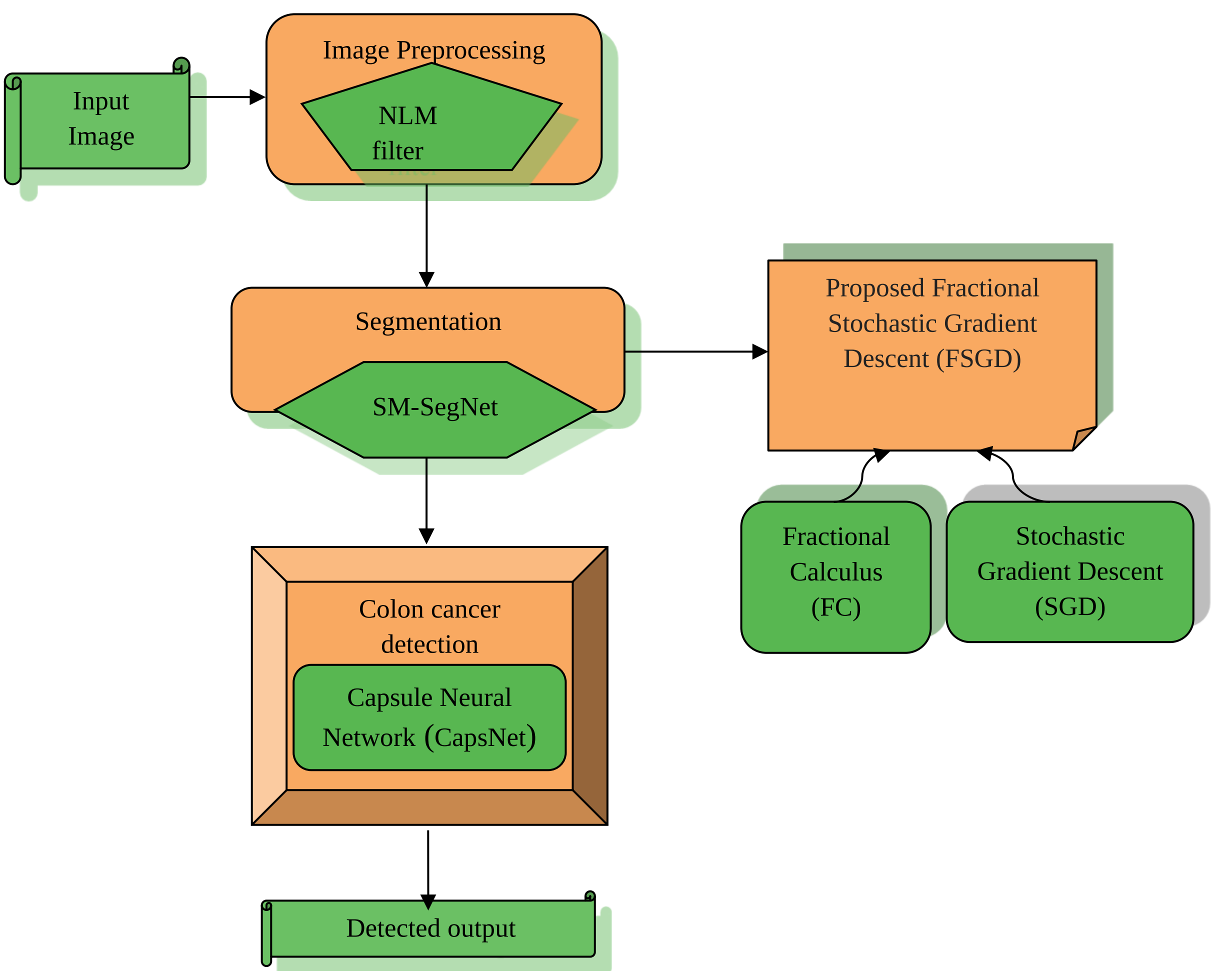
The prevailing colon cancer detection methods faced the challenges that are mentioned below.

- The DCNN model [1] had efficiently classified colon cancer at an early stage. But, it failed to enhance the classification and prediction accuracy by buiding up a DNN model with pre-processing framework on a big dataset with more labeled colon tissue.
- The CNN-VGGNet in [2] yielded better performance results. Yet, it failed in exploring the latest colon cancer dataset through well-organized preprocessing to enhance the performance in detecting colon cancer.
- Though the fast R-CNN model [5] had a promising ability to pick up high-risk colorectal features, it was tested only on a small sample dataset which was susceptible to heterogenicity of data and it diminished its applicability to clinical practice.
- The key challenges faced by prevailing colon cancer detection techniques were spatial heterogeneity within the tumor mass, lack of complex datasets with diverse colon cancer images, and deficiency in understanding of the development and progression of colon cancer cells.

3. Proposed FSGD SM-SegNet with CapsNet for colon cancer detection

The developed FSGD SM-SegNet with CapsNet to detect colon cancer consists of the following stages. Primarily, the input image is acquired from a dataset [16]. This acquired image is perprocessed for removing the noises in the image using NLM [11] filter. Later, colon cancer segmentation is carried out by the SM-SegNet [12] which is trained by the proposed FSGD. The proposed FSGD is the combination of FC [13] and the SGD [14]. The required region of the colon image is selected by segmentation. Finally, colon cancer detection is accomplished by CapsNet [15]. The diagram that illustrates the proposed FSGD SM-SegNet with CapsNet is displayed in figure 1.

Figure.1 Block diagram of the proposed FSGD - SM-SegNet and CapsNet for colon cancer detection.



3.1 Image acquisition

The presence of colon cancer is detected using the images acquired from the dataset, specified as S, which comprises m number of colonography images. The dataset is represented by

$$S = \{S_1, S_2, S_3 \ldots\ldots S_l \ldots\ldots S_m\} \tag{1}$$

where, S_l represent the l^{th} image considered for detecting colon cancer.

3.2 Image Preprocessing

The image S_l chosen for detecting colon cancer is preprocessed utilizing the NLM filter [11], in order to remove the noise present in it. The NLM filter preserves the sharp edges of the image efficiently. This NLM filter uses the redundancy of the image and considers its weighted average for its noise reduction. The estimated pixel value $F_{NLM}(l)$ is given by the formula as

$$F_{NLM}(l) = \sum u(l, j) x(j) \tag{2}$$

Here, the weighted value of $u(l, j)$ is determined by the similarity of the pixel l, j in search domain. The input to the NLM filter is S_l, whereas the outcome is S_q.

3.3 Image segmentation

The preprocessed image S_q is segmented to isolate the cancerous part in the image. The segmentation of the preprocessed colonographic image is executed by SM-SegNet [12] which is trained using the Proposed FSGD. The segmented output obtained is considered as S_t.

3.3.1 Architecture of SM-SegNet

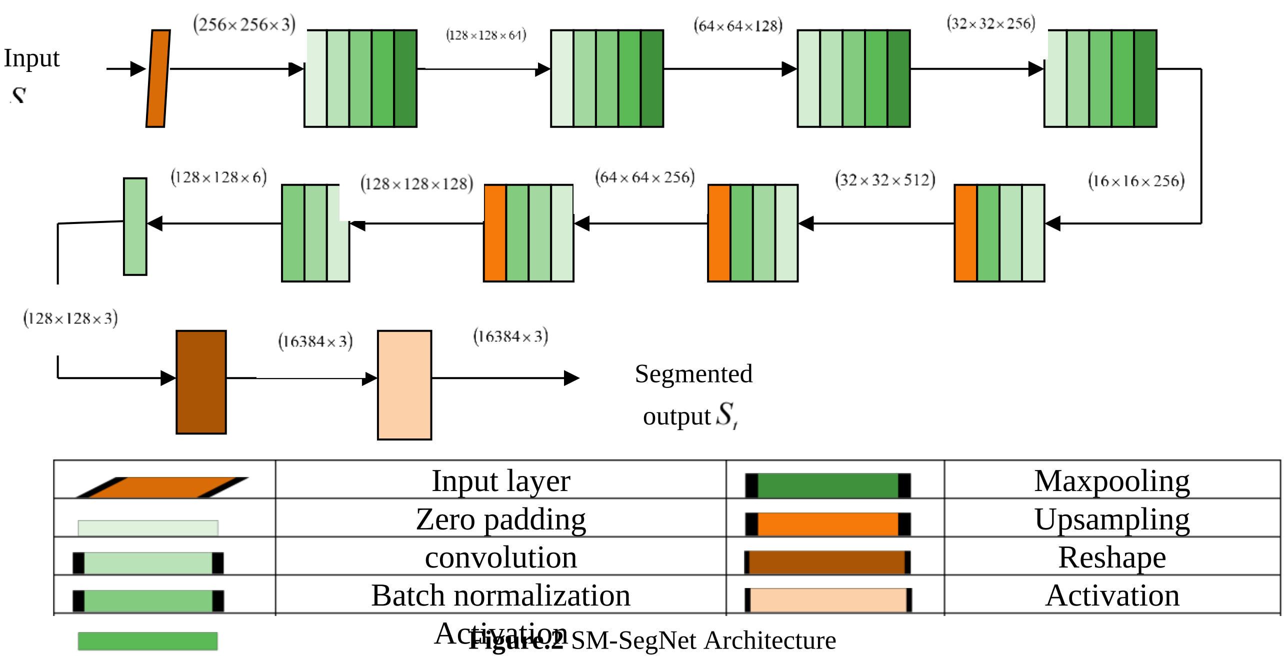


Figure.2 SM-SegNet Architecture

The SM-SegNet[12] consists of lengthy skip connections, fire modules, merged connections, left-leg and right-leg paths and so on. The left-leg path subsamples the input by using the maximum pooling layer for the extraction of discriminatory information and it is fed to the consequent encoder layer. Likewise, the decoding layers output is oversampled to the input size of right-leg path. Additionally, decoding layers as well as the right leg layer result in the integrated outcome which tackles the problem of vanishing gradient and fastens convergence. Hence the arrangement of the right and left legs enhances the training efficiency of the network. The merged connections are utilized for restoring the spatial information missed at the time of subsampling and advancing convergence through feature transfer between the encoder and decoder block. Furthermore, the lengthy skip connections were employed for stabilizing the update in gradients. The figure 2 shows the architecture of SM-SegNet.

3.3.2 Training SM-SegNet based on the proposed FSGD

The proposed FSGD is acquired by the combination of the FC[13] to the SGD[14]. The SGD utilizes the loss function gradients rather tha the entire training set to update the model variable. Therefore, SGD was faster than other gradient descent methods. FC is a mathematical model that is utilized for solving higher order derivate and integral functions based on Laplacian transform. The introduction of FC can improve the convergence speed as well as the optimization performance of the developed model, and the steps utilized to realize the FSGD are detailed below.

a)Initialization

The primary process is to initialize the parameters y of the SM-SegNet randomly in the search space.

b) Evaluation of fitness

The Proposed FSGD is used for training SM-SegNet. The system is said to be ideal, while the output of the SM-SegNet matches with the expected output anf hence, Mean Square Error (MSE) is considered as the objective. The MSE is expressed as,

$$Z = \frac{1}{h}\sum_{b=1}^{h}\left(H_s^{*} - H_s\right)^2 \tag{3}$$

where, h refers to the count of images employed for training the SM-SegNet, H_s^{*} symbolizes the estimated output and H_s designates the outcome of the SM-SegNet.

c) Update parameter

The parameter y is updated using the following equation,

$$y_{p+1} = y_p - kE'_d\left(y_p\right) \tag{4}$$

where, $E_d'\left(y_p\right)$ represents loss introduced in the model, y_p is the parameter at the p^{th} instance, and k is the step parameter.

Application of FC enhances the convergence rate of SGD, and from FC [13],

$$y_{p+1} - y_p = -kE'_d\left(y_p\right) \tag{5}$$

$$B^z\left[y_p + 1\right] = -kE_d'\left(y_p\right) \tag{6}$$

$$y_{p+1} - zy_p - \frac{1}{2}zy_{p-1} - \frac{1}{6}(1-z)y_{p-2} - \frac{1}{24}z(1-z)(2-z)y_{p-3} = -kE_d\left(y_p\right) \tag{7}$$

$$y_{p+1} = zy_p + \frac{1}{2} zy_{p-1} + \frac{1}{6}(1-z)y_{p-2} + \frac{1}{24} z(1-z)(2-z)y_{p-3} - kE'_d\left(y_p\right) \tag{8}$$

Here, $E'_d\left(y_p\right)$ gradient of E at y_p and z refers to the order of derivative.

d) Feasibility evalution

The updated solution is assessed for its feasibility by determining the fitness using equation (3).

e) Termination

The process of variable updation is repeated till the maximum number of iteration is attained.

3.4 Colon cancer detection

Colon cancer is detected by employing CapsNet [15]. The segmented image S_t acquired from the output of the segmentation phase is fed as input to the CapsNet which detects the presence of colon cancer in the segmented image. The CapsNet uses the component length of the activation vector in the capsule to depict the possibility of the presence of the required feature and employs the direction of the activation vector for the representation of parameters in resultant cases. The CapsNet consists of various capsules with specific meaning and direction. The CapsNet is employed here as it possesses the capability of identifying the entire entity.

3.4.1Architecture of Capsule Neural Network (CapsNet)

The key components of the CapsNet are the encoder and decoder, where the encoder has three layers and decoder has the three layers. The vector capsules are the lowest level capsules that take the small portions of the image as input. Here, the routing capsules are the higher level capsules that helps in detecting bigger and complicated problems. The outcome of the capsules are will be in the form of a vector and the length of every vector signifies the expected probability for the existence of the object. The Figure 3 potrays the architecture of the CapsNet.

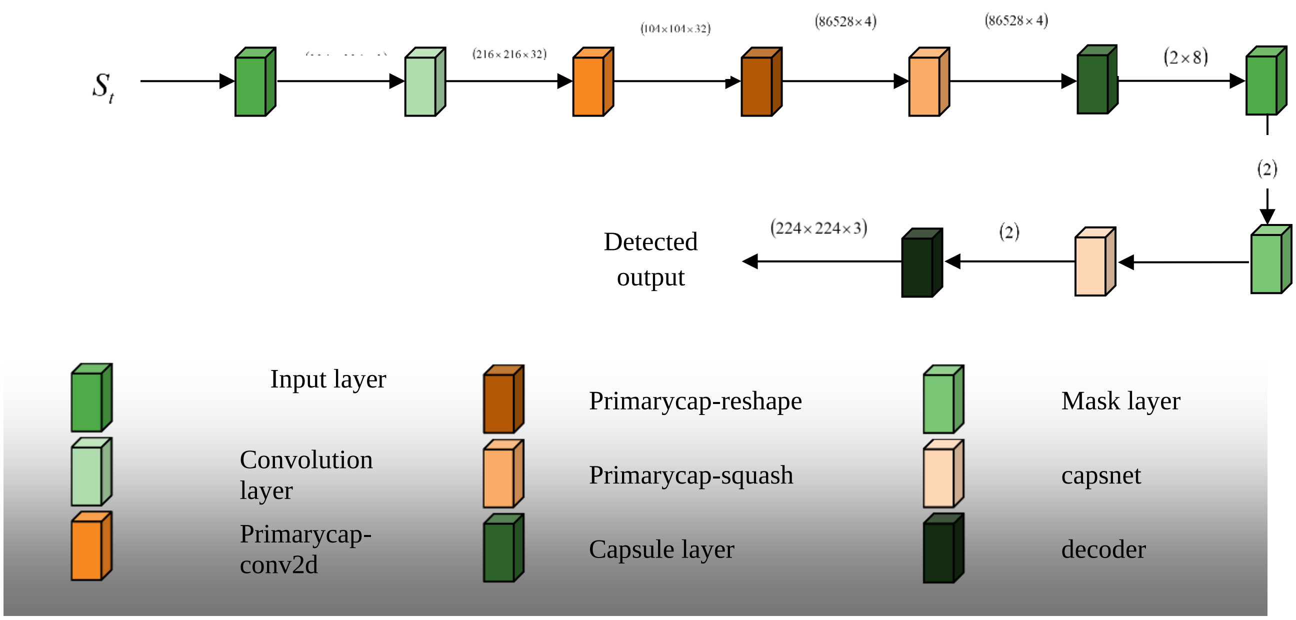


Figure.3 Architecture of CapsNet

4. Results and discussion

The proposed FSGD-SM-SegNet with CapsNet method for colon cancer detection is assessed employing various metrices. Then the performance is compared with the other conventional methods for colon cancer detection methodologies.

4.1. Experimental set-up

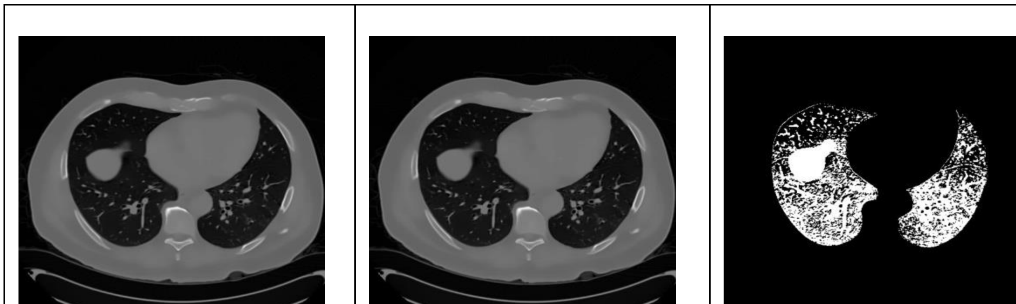
The developed colon cancer method named FSGD SM-SegNet with CapsNet is implemented by means of the Python tool.

4.2. Dataset description

The developed colon cancer detection method FSGD SM-SegNet with CapsNet used the images for colon cancer detection acquired from the CT colonography dataset [16], which is otherwise known as National CT Colonography Trial (ACRIN 6664) collection. It consists of 825 samples of CT colonography images accompanied by spreadsheet that includes polyp specifications with its position in the colon regions.

4.3. Experimental outcomes

The outcomes gained by testing the developed colon cancer detection method is displayed in figure 4. The figure 4a. presents the input image chosen for detection. The figure 4b. portrays the preprocessed image obtained from the output of the NLM filter. The segmented image from the outcome of the proposed FSGD SM-SegNet is exhibited in the figure 4c.



a.	b.	c.

Figure 4. Experimental results a. The input image b. The preprocessed image c. The segmented image.

4.4. Evaluation measures

The method introduced for colon cancer detection was assessed employing distinct evaluation measures namely specificity, accuracy and sensitivity.

a) Specificity: Specificity is the ability of the model to exactly predict the true negatives in each category. It is expressed as

$$Specificity = \frac{N_1}{N_1 + M_1} \tag{9}$$

where N_1 represents the true negatives and M_1 represent the false positives.

b) Sensitivity: The ability of the model to correctly predict the true positives in each category is the sensitivity. The sensitivity is expressed by

$$Sensitivity = \frac{M_2}{M_2 + N_2} \tag{10}$$

where M_2 represents the true positives and N_2 represent the false negatives.

c)Accuracy: Accuracy is the number of correct detections to the total number of detections made by the model.

$$Accuracy = \frac{N_1 + M_2}{M_1 + N_2 + N_1 + M_2} \tag{11}$$

4.5. Comparative techniques

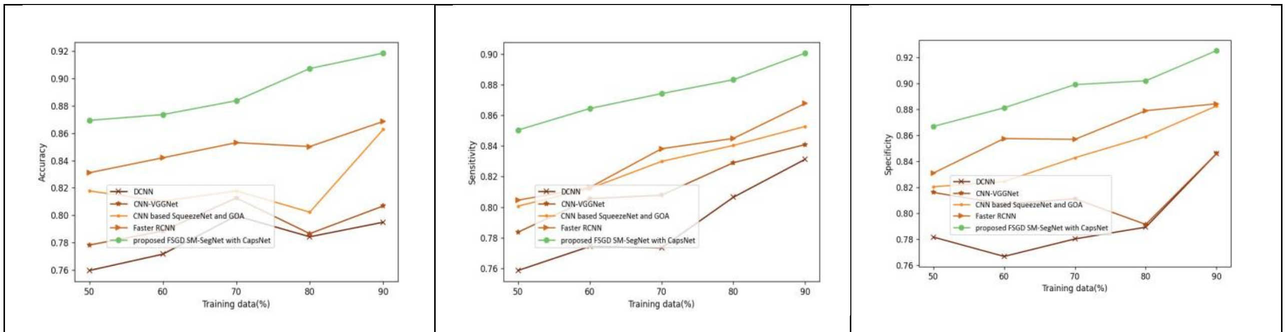
The developed FSGD SM-SegNet with CapsNet for colon cancer detection is compared with the conventional colon cancer detection methods namely DCNN [1], VGGNet [2], CNN based on SqueezeNet and GOA [3], and faster RCNN [5] for the assessment of the performance.

4.5. Comparative assessment

The comparative assessment part details the assessment of developed model's performance with a variety of methods employed for colon cancer detection on the basis of specificity, sensitivity and accuracy.

4.5.1. Comparative examination based on training data.

The performance of the developed FSGD SM-SegNet with CapsNet for detecting the colon cancer is examined comparably in this section and is revealed in Figure 5. Figure 5a. delineates the comparative analysis of the developed model with other comparative models based on accuracy . For training data of 90%, the accuracy acquired for DCNN, VGGNet, CNN based SqueezeNet and GOA, Faster RCNN and the developed FSGD SM-SegNet with CapsNet is 0.794, 0.809, 0.862, 0.868 and 0.918 correspondingly. The accuracy of FSGD SM-SegNet with CapsNet is 6.30% than the Faster RCNN. Later, analysis of developed method based on sensitivity is represented in Figure 5b. For the training data of 90%, the sensitivity of DCNN is 0.83, the VGGNet is 0.84, CNN based SqueezeNet and GOA is 0.85, Faster RCNN is 0.86 and that of the developed FSGD SM-SegNet with CapsNet is 0.90. The sensitivity of the proposed model is 6.86% higer than the CNN based SqueezeNet and GOA. Then, the developed technique is analyzed based on specificity and is displayed in Figure 5c. If considering the training data of 90% the specificity of the DCNN is 0.84, VGGNet is 0.845, CNN based SqueezeNet and GOA is 0.882, Faster RCNN method is 0.884 and the developed techniques is 0.925 correspondingly. Thus the specificity of FSGD SM-SegNet is improved by 4.77% than Faster RCNN.

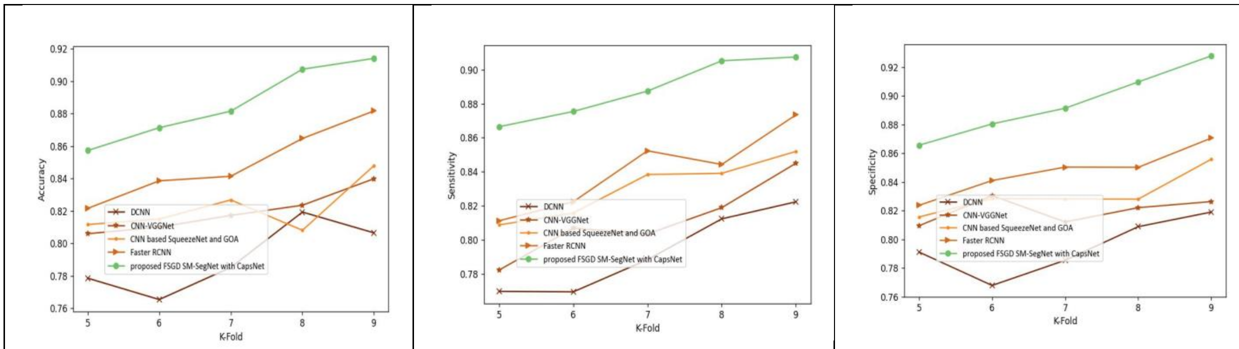


a. b. c.

Figure 5: Comparative examination of developed technique with the existing methods based on a. accuracy, b. Sensitivity, and c. Specificity based on training data.

4.5.2. Comparative assessment based on k-value

The performance of the developed FSGD SM-SegNet with CapsNet for detecting the colon cancer is examined comparatively in the current segment on the basis of k- value and is revealed in Figure 6. Figure 6a. reveals the comparative analysis of the developed model with other comparative techniques in terms of accuracy. For the k-fold value as 8, the accuracy acquired for DCNN, VGGNet, CNN based on SqueezeNet and GOA, Faster RCNN and the developed FSGD SM-SegNet with CapsNet is 0.819, 0.823, 0.808, 0.864 and 0.907 respectively. The of the developed model accuracy was improved by 4.71% than Faster RCNN. Afterwards, analysis of developed method with the comparative techniques based on sensitivity is revealed in Figure 6b. For the k-fold value as 9, the sensitivity of DCNN is 0.822, the VGGNet is 0.845, CNN based on SqueezeNet and GOA is 0.852, Faster RCNN is 0.873 and that of the developed FSGD SM-SegNet with CapsNet is 0.907. Then, the developed technique is analyzed based on specificity and is displayed in Figure 6c. If the k-fold value is considered to be 9, the specificity of the DCNN, VGGNet, CNN based SqueezeNet and GOA, Faster RCNN and the developed FSGD SM-SegNet with CapsNet are 0.818, 0.826, 0.855, 0.870 and 0.927 respectively. This shows that the specificity of the proposed model is enhanced by 9.64% than the VGGNet method.



a.	b.	c.

Figure 6: Comparative examination of the developed technique with the current methods based on a. accuracy, b. Sensitivity, and c. Specificity TNR based on k-fold.

4.6. Comparative discussion

The developed FSGD SM-SegNet with CapsNet's performance on the basis of diverse validation metrics namely accuracy, sensitivity and specificity is relatively conferred in the present segment with prevailing schemes for colon cancer. Table 1 portrays the comparative description of the developed method with the existing colon cancer detection techniques based on the accuracy, sensitivity and specificity considering the training data to be 90% and the k-fold to be 9. Table highlights that a high accuracy, sensitivity as well as specificity is accomplished by the developed FSGD SM-SegNet with CapsNet. The accuracy of the existing techniques namely, DCNN, VGGNet, CNN based on SqueezeNet and GOA, Faster RCNN and the developed model are 0.794, 0.806, 0.862, 0.868, and 0.918 respectively. Further, the existing schemes, like DCNN, VGGNet, CNN based on SqueezeNet and GOA, and Faster RCNN measured sensitivity of 0.822, 0.845, 0.852, and 0.873 while the FSGD SM-SegNet with CapsNet measured high sensitivity of 0.907. The FSGD SM-SegNet with CapsNet recorded high specificity of 0.927, while the value attained by DCNN is 0.818, VGGNet is 0.826, CNN based on SqueezeNet and GOA is 0.855, and Faster RCNN is 0.870. Due to the addition of the FC in SGD, the convergence speed was increased and thus the performance of segmentation was improved. Moreover, the detection using CapsNet enabled identifying the colon cancer correctly, thereby attaining improved performance.

Table 1. Comparative description of the introduced method

Variation	*Metrics*	*DCNN*	*VGGNet*	*CNN based SqueezeNet and GOA*	*Faster RCNN*	*Proposed FSGD SM-SegNet with capsNet*
Training data	*Accuracy*	79.4	80.6	86.2	86.8	**91.8**
	sensitivity	83.1	84	85.2	86.7	**90**
	specificity	84.5	84.5	88.2	88.4	**92.5**
k-fold value	*Accuracy*	80.6	83.9	84.8	88.1	**91.4**
	Sensitivity	82.2	84.5	85.2	87.3	**90.7**
	Specificity	81.8	82.6	85.5	87	**92.7**

4.6.3 Comparative assessment based on segmentation accuracy

The performance of the developed FSGD SM-SegNet for segmentation is examined comparatively in the current segment on the basis of segmentation accuracy. Various methods like Comparative Segmentation Network (CompSegNet) [2], Glandular segmentation method (gland method) [5], the UNet model with attention vector (Att-UNet) [17] are considered to evaluating the proposed scheme. The assessment of the FSGD SM-SegNet based on segmentation accuracy is revealed in Figure 7. For the training data of 90%, the segmentation accuracy acquired by CompSegNet, gland method, Att-UNet and the developed FSGD SM-SegNet are 0.187, 0.853, 0.860 and 0.913 respectively. From the above mentioned output values its clear that the developed FSGD SM-SegNet method had higher segmentation accuracy which is about 5.85% higher than the Att-UNet method.

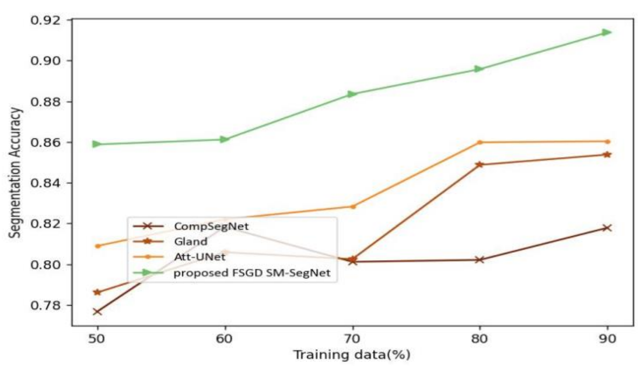


Figure.7 Comparative assessment based on segmentation accuracy

5. Conclusion

In this paper, a novel segmentation technique using SM-SegNet trained using the proposed FSGD is developed for accurate colon cancer detection. This segmentation facilitates the optimal selection of the required image area so that the detection accuracy is increased. The elimination of noise and unnecessary artifact present in input colography image is performed by means of the NLM filter in the preprocessing step. The preprocessed image is then segmented. And finally, the colon cancer detection is accomplished utilizing CapsNet classifier. This newly developed methodology is later examined using metrics like sensitivity, accuracy and specificity. This shows that the developed approach surpass the comparative techniques by gaining higher accuracy, sensitivity and specificity. In this method, a high accuracy of 0.914, sensitivity and specificity of about 0.907 and 0.927 respectively are acheived, thus signifying the superiority of the developed method in colon cancer detection. Moreover, enhanced segmentation methods and hybrid classifiers might be incorporated for the more accurate and faster colon cancer detection in future.

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