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# Combined Feature Learning And CNN For Polyp Detection In Wireless Capsule Endoscopy Images

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***Abstract*** *- There is a high probability for the polyps of the small intestine to turn into a malignant tumor. So, it is mandatory to identify these polyps in the early stage and remove them. This would increase the patient's survival rate many times. With the tremendous growth of the technology, Wireless Capsule Endoscopy (WCE) is viewed as an achievement in the medical field. WCE makes it easy, painless, and inexpensive to view an internal body that humans cannot see. However, the primary disadvantage of wireless capsule endoscopy is the poor image quality. Additionally, the shape, color, and texture of the human gastrointestinal (GI) tract resemble polyps. Hence, certain types of polyps cannot be identified even by a well-trained doctor. For this reason, a computer-aided polyp segmentation remains a problem to be solved. In this proposed research, the Combined Feature Learning (CFL) and Convolutional Neural Network (CNN) has been used to develop an automated polyp detection system. WCE images have been augmented to improve the training efficiency of the proposed CFL-CNN model. Furthermore, high and low level feature learning has been used in this proposed method to reduce the False Positive (FP) rate. The experimental results demonstrate that high-level features and image augmentation significantly reduce the FP intensity. This shows a significant improvement in overall performance in terms of precision, sensitivity, specificity, and recall. Additionally, the experiment results indicate that training the proposed CFL-CNN model requires a small amount of time and computational resources.*

**Keywords** — *Wireless Capsule Endoscopy, Image Segmentation, Image Pre-Processing, CNN, Polyp Detection, Deep Learning.*

## I. INTRODUCTION

The small intestine is an important part of the organism's digestive system [6]. It is located between the large intestine and the stomach. The figure of the human digestive system is shown in Fig. 1. The small intestine performs the important function of digesting food by isolating water, proteins, minerals, fats, and carbohydrates separately [7]. It is divided into three parts: duodenum, jejunum, and ileum. This is where most of the food is finally absorbed. There is very little chance of tumors in the small intestine. Less than five percent of all cancer types occur in the small intestine [8]. Most of them occur in the colon but most cancer that comes into the human digestive system is potentially life-threatening [9][10]. Most of the diseases inside the human belly such as tumors, ulcers, and bleeding if identified early they can be controlled and cured easily [11]. Simultaneously it is very complicated to identify these diseases in the early stage. Many technologies are being applied in the medical industry for the same such as angiography, radiography, ultrasonography, etc. Nevertheless, these technologies could not yield any good results.

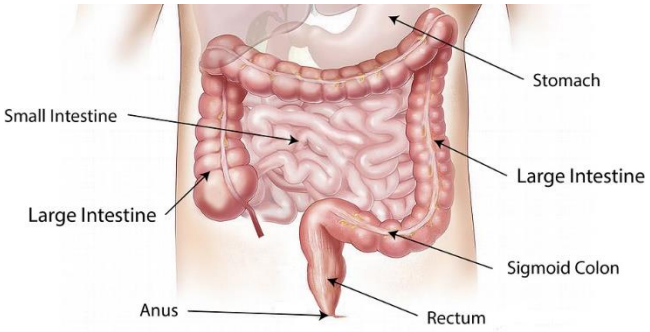


**Fig.1. Human digestive system.**

In India cancer is being formed as a grave health problem for many past decades. Moreover, its incidence rate is rising day by day. Polyp must control its initial stage. Untreated polyp can probably be turned into a malignant tumor [12]. The Wireless Capsule Endoscopy (WCE) has become a boon to the medical industry [14]. The WCE was developed in 1997 by Gabi Iddan and Paul Swain. WCE is a capsule-shaped portable photographic device. The capsule size is 2.6 cm long and 1.1 centimeters in width. It is a high-tech wireless camera that incorporates modern technologies [13]. WCE image shown in fig 2. This WCE method is carried out at many medical centers, scientific research centers, and oncology clinics in India.

**Fig.2. Wireless Capsule Endoscopy image.**

Through its advanced technology, the process of investigating gastrointestinal tracts has been made easy. The following diseases can be easily diagnosed with the help of WCE: crohn's disease, gastrointestinal bleeding, diagnose cancer, examine esophagus ,diagnose celiac disease, and screen for polyps [15]. The WCE delivers patients with frictionless and painless observation to the internal organs. For that reason, it has got much welcome from the patients. Simultaneously, when compared with wired endoscopy, low frame rate, limited working time and low image resolution remain as the problems unsolved. Through the low quality, image is very complicated to diagnose the abnormalities in these images even by a well-experienced physician. Automatic polyp recognition is a difficult task because the gastrointestinal tract has a polyp-like structure and the polyp is formed in a variety of colors, textures, and shapes. As a result, the likelihood of a false positive rate is increasing. Hence wireless-capsule polyp segmentation remains an important research problem. For this polyp segmentation number of attempts is being done over the years. Still, it remains a challenging task. Figure.3 shows wireless capsule endoscopy images with polyp and non- polyp.

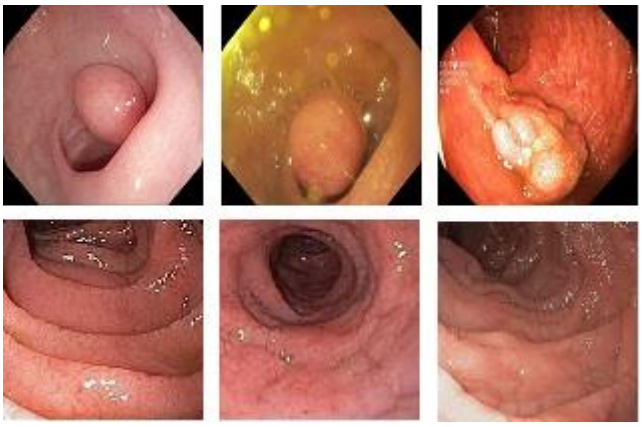

**Fig.3 WCE images with polyp and non- polyp.**

Convolutional Neural Network (CNN) or ConvNet is a sub-module of deep learning [16][20]. CNN can quickly spot hidden visuals that are invisible to the human eye. Due to this CNN is widely used in medical image processing systems [17]. However, there are a variety of issues that arrives using CNN to process WCE images. In particular, WCE captures the GI tract from multiple angles. Usually processing the different angle images through CNN, accuracy is greatly affected. Second, training a CNN model consumes a significant amount of computing resources. Thus, to train a CNN model, a very efficient Graphical Processing Unit (GPU) unit is required. The primary goal of this research is to develop a lightweight and highly accurate automated polyp detection system for the healthcare sector.

This proposed WCE polyp detection method's key contributors are.

1. Image augmentation, thereby developing a high accurate polyp detection system from a limited amount of training images and reducing the computational time and resource used for model training.

2. Extracting meaning full high-level features from WCE images with polyp-like structure, color, and shape thereby reducing False Positive (FP) rate multiple times.

The literature survey is covered in section 2 of this article. Section 3 proposed methodology is explained. In section 4, the proposed polyp segmentation method is evaluated by real-time medical image data-set. Finally, this GI tract polyp detection method has been concluded, and further future research has been discussed.

## II. LITERATURE REVIEW

This section discusses in-depth the newly developed polyp classification system using deep learning methods.

Mustain Billah et al [1]. suggested a computerized approach for detecting gastrointestinal polyps using video endoscopy. According to this method, first the convolutional neural network and color wavelet features of the video frames are extracted. The linear support vector machine (SVM) is trained by these extracted features. This method reduces the false positive rate caused by color features. However, this method failed to prevent the false positive rate caused by the polyp similar features of the GI tract.

Xiaoyong Yang et al [2]. developed a method for colon polyp detection and segmentation by using mask regions convolutional neural network (MRCNN). This method employs a precise region of interest technique to locate polyps. In MRCNN, features are extracted via the backbone network. The region proposal network is used to identify candidate regions. This method does not use image augmentation to fix fewer datasets problems so there is a chance of over fitting.

MahmodulHasan et al [3]. developed a gastrointestinal polyp detection method. The features of the GI tract are extracted through two methods, the Convolutional Neural Network (VGG19 model) and the contourlet transform. Support vector machine is used to classify polyp and non-polyp. A polyp region marking algorithm was developed in this study to mark around the polyp region.

Rafid Mostafiz et al [4]. developed a classification method for gastrointestinal polyps based on convolutional neural networks and bi-dimensional empirical mode decomposition (BEMD). This approach makes use of the endoscopic vision challenge and Alcala datasets. SVM is employed for polyp categorization in this strategy. However, extracted frames are not performed image augmentation so accuracy issues are certain to arise.

YOUNGHAK SHIN et al [5]. used Conditional Adversarial Networks to develop a system for detecting abnormal colon polyps. Conditional Adversarial Networks is a deep learning architecture based on the U-Net. Adopting dilated convolutions used in encoding layers and image resizing with the convolution strategy used in decoding layers. Although this method is efficient, it requires significant processing resources during training.

## III. PROPOSED METHODOLOGY

The proposed polyp segmentation method has two main image processing modules: image pre-processing and the proposed CFL-CNN based polyp identification module. The overall architecture of the proposed method is illustrated in figure 4.

### A. *Image Pre-Processing*

Image pre-processing plays an important role in medical image segmentation [18]. Medical images contain a wide variety of noise, contrast and variance. WCE is commonly available in a number of configurations. As a result, there are variations in the quality and size of the images generated by WCE. To obtain a better classification result, must include these wireless endoscopy images with excellent pre-processing techniques. In this study, image preprocessing is divided into three sections: image resizing, contrast enhancement, and image augmentation.

### *B. Image Resizing*

When the configuration of WCE varies, there is a difference in the size and quality of the WCE images. When the size of the WCE images is large, it takes a lot of time and computational power to build a model. In this proposed research, the image is resized to 320×320×3 size before training and testing.

### *C. Contrast Enhancement*

Due to a lack of light penetration, human internal organs are typically very dark. As a result, the images captured by WCE are likely to be extremely dark. When this image is processed in its raw state, the resulting image has a very low degree of accuracy. Therefore, a special contrast enhancement technique must be used to build a polyp classification system with a high degree of accuracy. In this proposed method, unsharp filter, blind deconvolution, and Contrast Limited Adaptive Histogram Equalization (CLAHE) methods have been used for WCE image enhancement. The unsharp mask filter and blind deconvolution are used to restore blurred WCE images. The CLAHE method is used to restore images and balance the contrast.

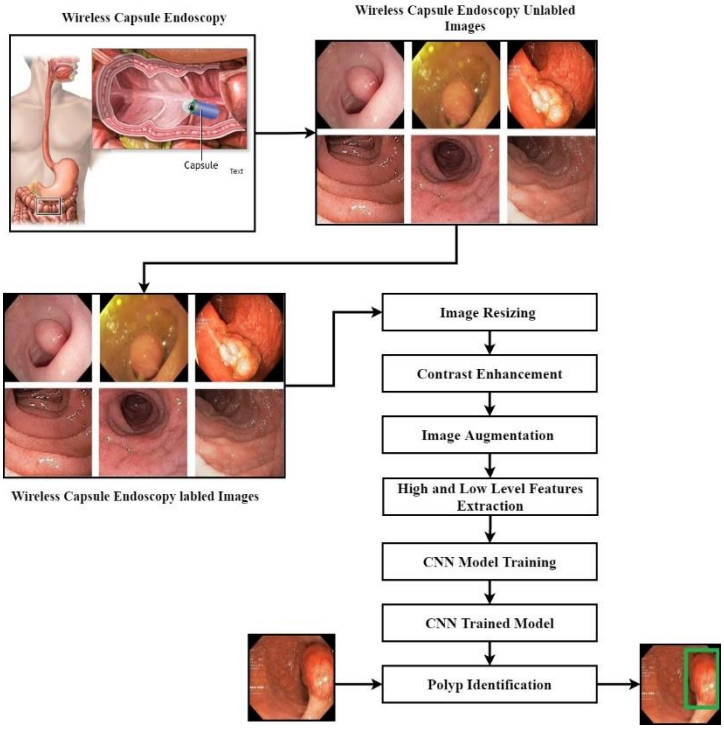


**Fig 4 Overall architecture of the proposed WCE polyp detection method.**

### *D. Image augmentation*

WCE captures images from a number of angles. Due to the different angles of the WCE images, CNN's classification accuracy is likely to suffer. Image augmentation is used in this proposed research to compensate for the loss of accuracy caused by the different angles of WCE images. In image augmentation, the image is rotated 90, 180, 360 degrees, as well as flipped horizontally and vertically. The results of the image augmentation are shown in figure 5. Through image augmentation, the high accurate polyp classification system can be developed with a limited number of training images. Additionally, image augmentation can significantly reduce the amount of computing power required for CNN model training.

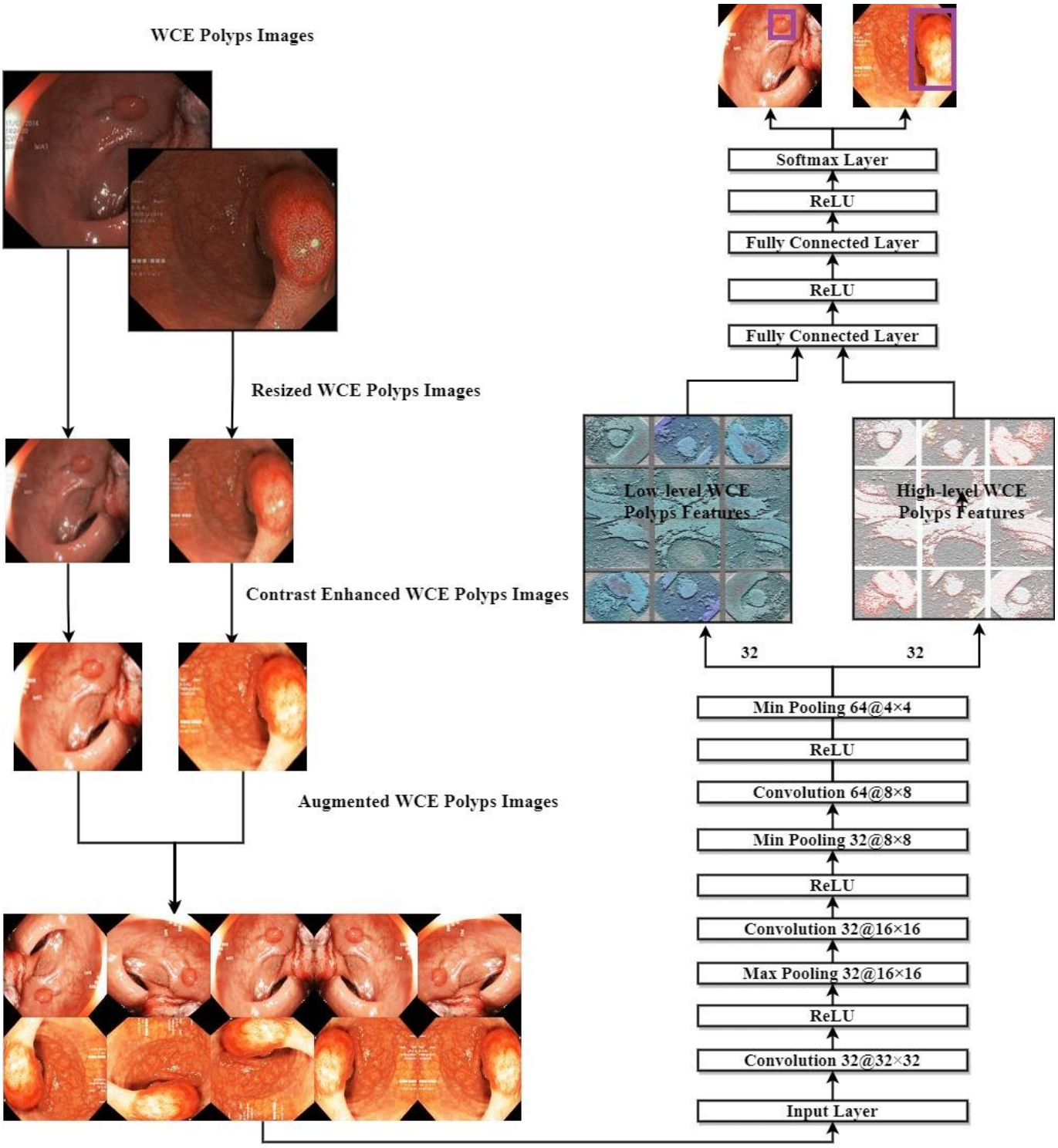


**Fig 5. Architecture of the combined feature learning-based convolutional neural network polyp detection in wireless capsule endoscopy images.**

### *E. Typical CNN Architecture*

Traditional machine learning algorithms have many drawbacks when it comes to the segmentation and classification of medical images. Thus, to enhance the accuracy of medical image segmentation, this proposed WCE polyp detection method makes use of the well-known Convolutional Neural Network. CNN is a feed-forward type of neural network architecture. It usually consists of five main layers: input layer, convolutional layer, pooling layer, fully connected layer, and output layer [12][13]. In this proposed study the preprocessed WCE image matrix is fed into the CNN. Figure 5 illustrates the architecture of the proposed combined feature learning polyp detection system for wireless capsule endoscopy images.

### *F. Combined Feature Learning*

The primary objective of this module is to correctly combine high-level and low-level features from WCE images in order to isolate polyps with a variety of structures and identify polyps at a very early stage. The appearance of the GI tract is most likely to resemble a polyp, and more than 90% of the color of the polyp images and the color of the GI tract would be identical. As a result, it is extremely difficult to separate the polyp from the surface of the GI tract. Low-level features contain the most comprehensive information's about WCE images, whereas high-level features provide the WCE images semantic information's. The proposed combined feature learning architecture is depicted in figure 1. In this proposed CFL-CNN method, the highest feature values and lowest feature values of WCE images are transferred to the output layer through convolutional layers. This CFL architecture is made up of three convolutional layers (C1, C2, and C3) as well as three pooling layers (P1, P2, and P3). CNN's input size is 32×32 ×3, where 3 represents the RGB color channel. The convolutional layer kernel size is set to 5x5x2 and the pooling layer kernel size is set to 3x3x2. After this convolution and pooling process, two feature vectors $\overrightarrow{fh} = 32$ and $\overrightarrow{fl} = 32$ will be obtained. Where $\overrightarrow{fh}$ denotes the highest feature values in WCE images and $\overrightarrow{fl}$ denotes the lowest feature values in WCE images. The following formula combines these two feature vectors. Finally, two fully connected layers and a softmax layer are used to identify polyps.

$$CF = \sqrt{\left|\overrightarrow{fh}\right|^2 + |\overrightarrow{fl}|^2 + 2|\overrightarrow{fh}||\overrightarrow{fl}| \cos\theta} \quad (1)$$

CF is the combined features. The RLU activation function using the CNN-CFL method is described by formula 2. This converts the extracted negative values from WCE images to 0. The proposed method's process flow is given in algorithm1.

$$f(x) = \max(0, x) \quad (2)$$

***Algorithm1***

***Input****: WCE GI Polyp and Non-Polyp images.*
***Output****: Polyp detection.*
***Step1****: Image resizing (*320×320×3*).*
***Step2****: Contrast enhancement.*
***Step3****: Image augmentation (Flipping and rotation).*
***Step4****:Low-level and high-level feature extraction from normalized WCE images using convolution and pooling operation.*
***Step5****: Combine the feature vectors* $\overrightarrow{fh}$ *and* $fl$.

$$CF = \sqrt{\left|\overrightarrow{fh}\right|^2 + |\overrightarrow{fl}|^2 + 2|\overrightarrow{fh}||\overrightarrow{fl}| \cos\theta}$$

***Step6****: Trained the model using CF.*
***Step7****: Evaluate the model.*
***Step8****: Validate the model* (Accuracy, PRE, REC, and F1 score).

## VI. RESULTS AND DISCUSSIONS

### *A. Dataset and System Configuration*

In this research, randomly selected 1396 WCE images from 187 patients with gastrointestinal polyps are used for CNN CFL-CNN model training. This includes 872 polyp affected images and 524 non-polyp images. All these images were collected from the scan center in the Kims Hospital Trivandrum. Furthermore, 52% of these images were taken from male patients and the majority were between the ages of 50 and 60 years. The images are all pixel size of 620×480. As shown in table 1, divided this image data set into a 3: 1 ratio for training and testing. Accordingly, 628 polyp images and 384 non-polyp images were taken for training and 244 polyps affected and 140 non-polyp images were taken for testing. To perform this experiment Matlab 2016 and Windows10 have been used. A computer with Intel i5 1-8 GHz processor, 8 GB RAM, 1 TB storage space, and NVIDIA GeForce GPU is also used to execute this CFL-CNN-based GI polyp detection system.

**Table1 Polyp Dataset Images Details**

| Data Split | Num. of Polyp Images | Num. of Non-Polyp Images |
|---|---|---|
| Training | 628 | 384 |
| Testing | 244 | 140 |

### *B. Evaluation Criteria*

There are two primarily class labels used in this suggested segmentation method, namely polyp, and non-polyp. To measure its accuracy four main parameters have been used. They are True Positive, False Positive, True Negative and False-negative.

**True Positive**: If the proposed framework correctly finds polyp then it is true positive. It is referred to as TP.
**True Negative**: If the proposed framework correctly finds out there is no polyp that means it is true negative. It is

referred to as TN.

**False Positive**: If the proposed framework incorrectly shows the present of polyp then it is false negative. It is referred to as FP.

**False Negative**: if the proposed framework incorrectly shows that there is no polyp then it is false positive. It is referred to as FN.

These four parameters are used to calculate the following four metrics: Accuracy, Precision, Recall and F1-Score [19].

**Accuracy** is an important metric use to evaluate the proposed CNN-based classification model. This is usually defined by formula 3. Formula 4 is used to calculate this.

$$Accuracy = \frac{Number\ of\ Correct\ \ Predictions}{Total\ Number\ of\ Predictions} \qquad (3)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (4)$$

**Precision** is the term used to define how positive identification is correct in classifications. The precision is calculated by Formula 5.

$$PRE = \frac{TP}{TP+FP} \qquad (5)$$

**Recall** refers to the classifier in which propositions are correctly identified as actual positives. This is calculated by formula 6.

$$REC = \frac{TP}{TP+FN} \qquad (6)$$

**The F1 score** is used to measure the classifier's test accuracy. Is a function of Precision and Recall. It is calculated by Formula 6.

$$F1 = 2\ X\ \frac{Precision \times Recall}{Precision+Recall} \qquad (7)$$

### *C. Training the CFL-CNN*

The proposed CFL-CNN model is trained by the polyp images mentioned in table 1. According to the table1, 628 polyp images and 384 non-polyp images are taken for training the CFL-CNN model. In general, training a deep learning model with a limited number of images, efficiency is likely to decrease. Due to the small number of training images, the chances of developing an over fitting problem are very high. To address this shortcoming, WCE polyp images have been augmented. The images are rotated and flipped in different directions to accomplish image augmentation. This will significantly reduce the false positive rates. After the image augmentation, the training images are increased by 5060. Even if the data set is enlarged, there is a slight chance of an over fitting problem. To address this problem, high and low-level features are extracted from the augmented dataset using convolution and pooling layers. After that efficiently combine the extracted WCE polyp and non-polyp features and train the model. Moreover, the Adam optimizer is used to further increase the training speed of the CFL-CNN GI tract polyp detection model. The model's learning rate is set to 0.001 and the epoch is set to 150.

### *D. Results analysis*

The performance of these proposed algorithms has been evaluated with state-of-art CNN methods. We use the following CNN methods: FCN-AlexNet, FCNGoogleNet, FCN-VGG, FCN-ResNet-50, FCN-ResNet-101 and FCN-ResNet-152. For a better comparison, these state-of-art CNN methods are experimentally implemented and their performance metrics are compared with the proposed CNN algorithm. The experimental values of proposed and state-of-the-art methods are summarized in Table 2 and Table 3.

In this experiment, 344 WCE images are being used for comparative analysis, it includes 244 polyp images and 140 non-polyp images. The CFL-CNN method's TP-Rate is compared with the traditional deep learning approaches. Figure 6a illustrates this, it is clear that the proposed CFL-CNN has a very high polyp detection efficiency. The comparative results of the FP-Rate are given in figure 6b. According to the figure, CFL-CNN's FP-Rate is very low. This definitely improves the prediction accuracy of CFL-CNN. Next to CFL-CNN, ResNet -101 and 152 have a higher FP-Rate. Figure 6c illustrates the TN-Rate comparison results. The findings indicate that the TN-Rate of CFL-CNN is more extreme than the traditional deep learning approaches. Figure 6d illustrates the FN-Rate of CFL-CNN. The figure demonstrates that CFL-CNN has a low FN-Rate.

**Table 2 FP,FN, TN and FN details of CFL-CNN and traditional deep learning methods.**

| Networks | TP | FP | TN | FN |
|---|---|---|---|---|
| FCN-AlexNet | 219 | 25 | 117 | 23 |
| FCNGoogleNet | 204 | 40 | 131 | 9 |
| FCN-VGG | 207 | 37 | 119 | 21 |
| FCN-ResNet-50 | 216 | 28 | 121 | 19 |
| FCN-ResNet-101 | 192 | 52 | 117 | 23 |
| FCN-ResNet-152 | 197 | 47 | 111 | 29 |
| CFL-CNN | 234 | 10 | 135 | 5 |

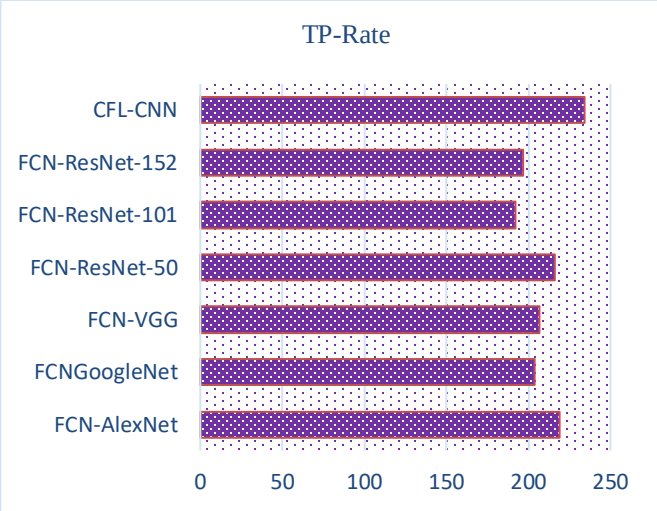


**Fig 6a. TP-Rates of CFL-CNN and traditional deep learning methods.**

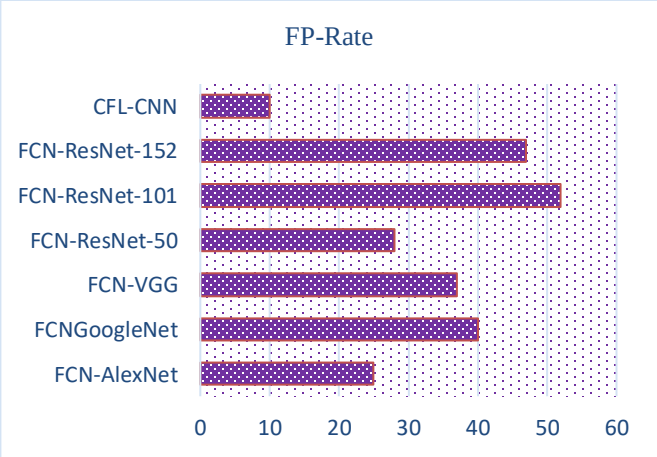


**Fig 6b. FP-Rates of CFL-CNN and traditional deep learning methods.**

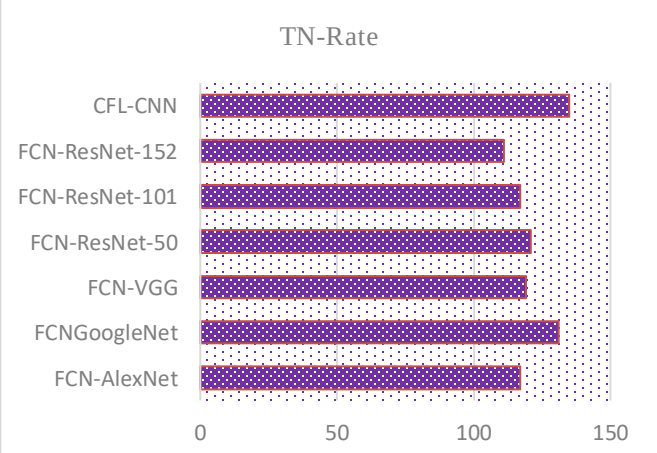


**Fig 6c. TN-Rates of CFL-CNN and traditional deep learning methods.**

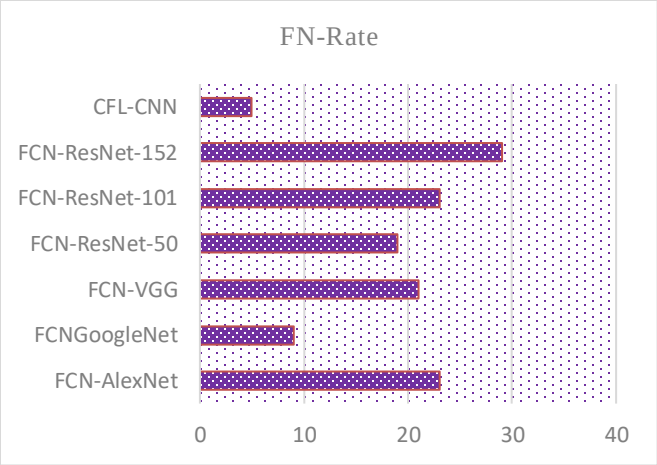


**Fig 6d. FN-Rates of CFL-CNN and traditional deep learning methods.**

**Table 3 accuracy measurements of the CFL-CNN and traditional deep learning methods.**

| Networks | Accuracy% | Pre% | Rec% | F1-Score% |
|---|---|---|---|---|
| FCN-AlexNet | 87.5 | 89.75 | 90.49 | 90.11 |
| FCNGoogleNet | 87.23 | 83.60 | 95.77 | 89.27 |
| FCN-VGG | 84.89 | 84.83 | 90.78 | 87.70 |
| FCN-ResNet-50 | 87.76 | 88.52 | 91.91 | 90.18 |
| FCN-ResNet-101 | 80.46 | 78.68 | 89.90 | 83.65 |
| FCN-ResNet-152 | 80.20 | 80.73 | 87.16 | 83.8 |
| CFL-CNN | 96.09 | 95.90 | 97.90 | 96.88 |

Comparative analysis was performed on the outcomes obtained using both the conventional and proposed deep learning methods. The proposed method's accuracy results are shown in Table 4, and the comparative results are shown in Figure 8 a, b, c, and d, respectively. The proposed approach seems to be very effective based on the research findings. CFL-CNN reaches 96.09 percent accuracy, as shown in Figure 8a. The proposed method's precession results are shown in figure 8b. The CFL-CNN method achieves a precession rate of 95.9 percent. This is accompanied by FCN-Alexnet, which reaches a precession rate of 89.75 percent. The recall rate comparison results are shown in Figure 9c and CFL-CNN has a recall rate of 97.9 percent. Additionally, CFL-CNN receives an F1-score of 96.88 percent. Finally, the training period for the CFL-CNN model is estimated. Due to the small data set and effective pre-processing techniques used, the CFL-CNN approach needs less time to train the model. The test results confirm

this.

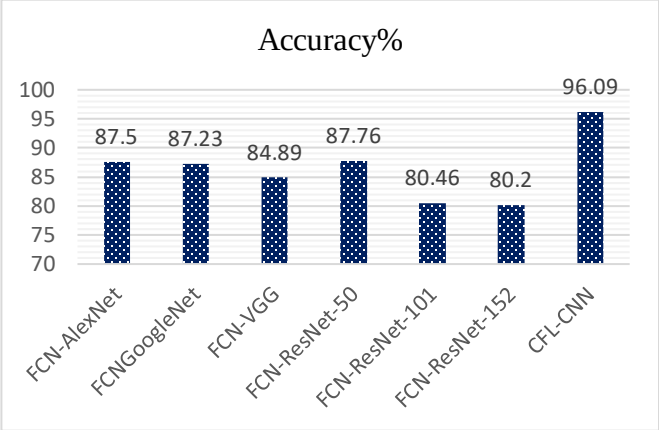


**Fig 7a. Accuracy results of CFL-CNN and traditional deep learning methods.**

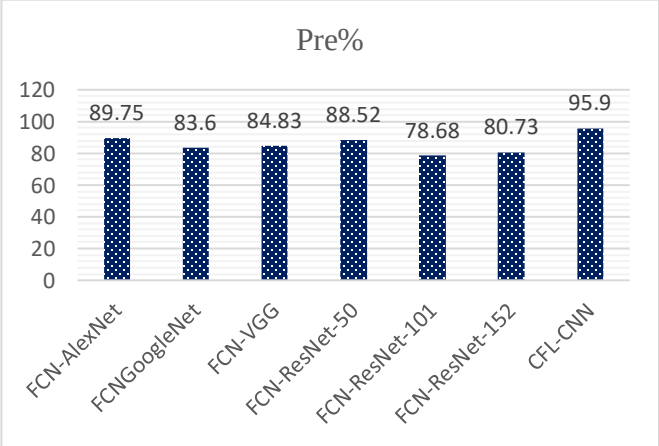


**Fig 7b. Precession results of CFL-CNN and traditional deep learning methods.**

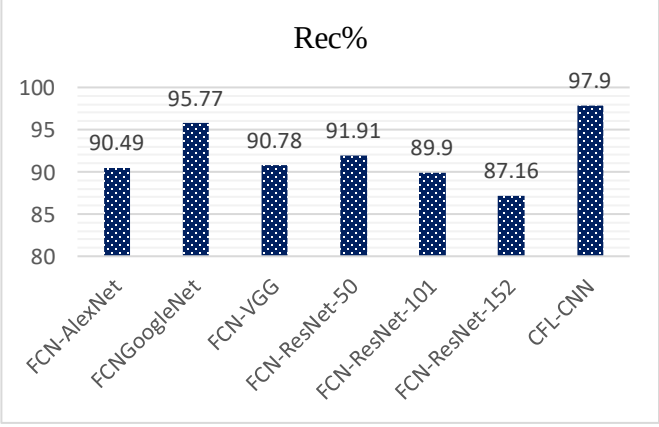


**Fig 7c. Recall results of CFL-CNN and traditional deep learning methods.**

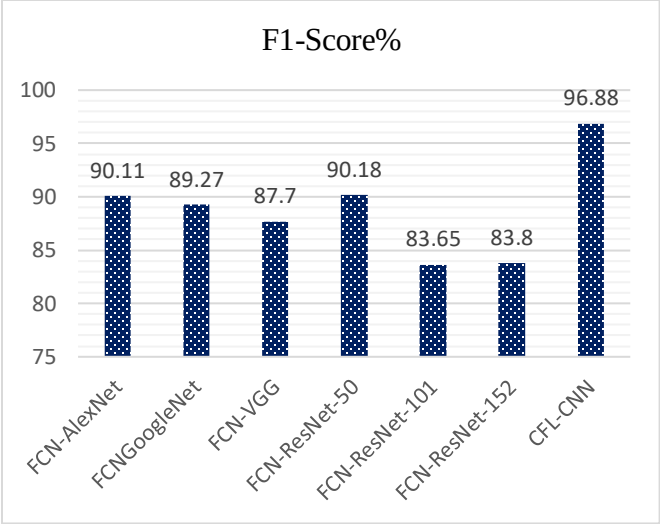


**Fig 7d. F1-Score results of CFL-CNN and traditional deep learning methods.**

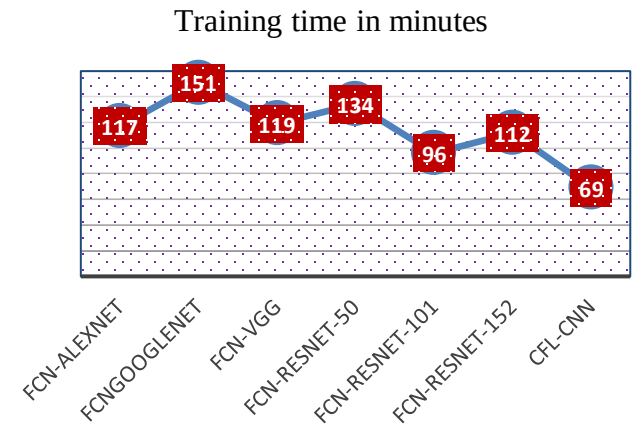


**Fig 8. Training time measurements of CFL-CNN and traditional deep learning methods.**

CFL-CNN requires 69 minutes to train the model, whereas Googlenet requires longer time. Figure 9 depicts the training time for CFL-CNN and deep learning approaches. Figure 9 shows the correctly classified results and incorrectly classified results produced by the proposed method. According to this proposed research, the possibility of polyp misclassification is extremely low it is described in detail by figure 9. High light intensity images, the shape of the GI tract is similar to the polyp, and zoomed polyp images are slightly more chances of misclassification. The proposed method's misclassification percentage is given in figures 9c1, 9c2, 9c3, and 9c4. The non-polyp images in figures 9d1, 9d2, 9d3, and 9d4 are identical in terms of polyp shape, texture, and color. The possibility of misclassification in such images is a bit high.

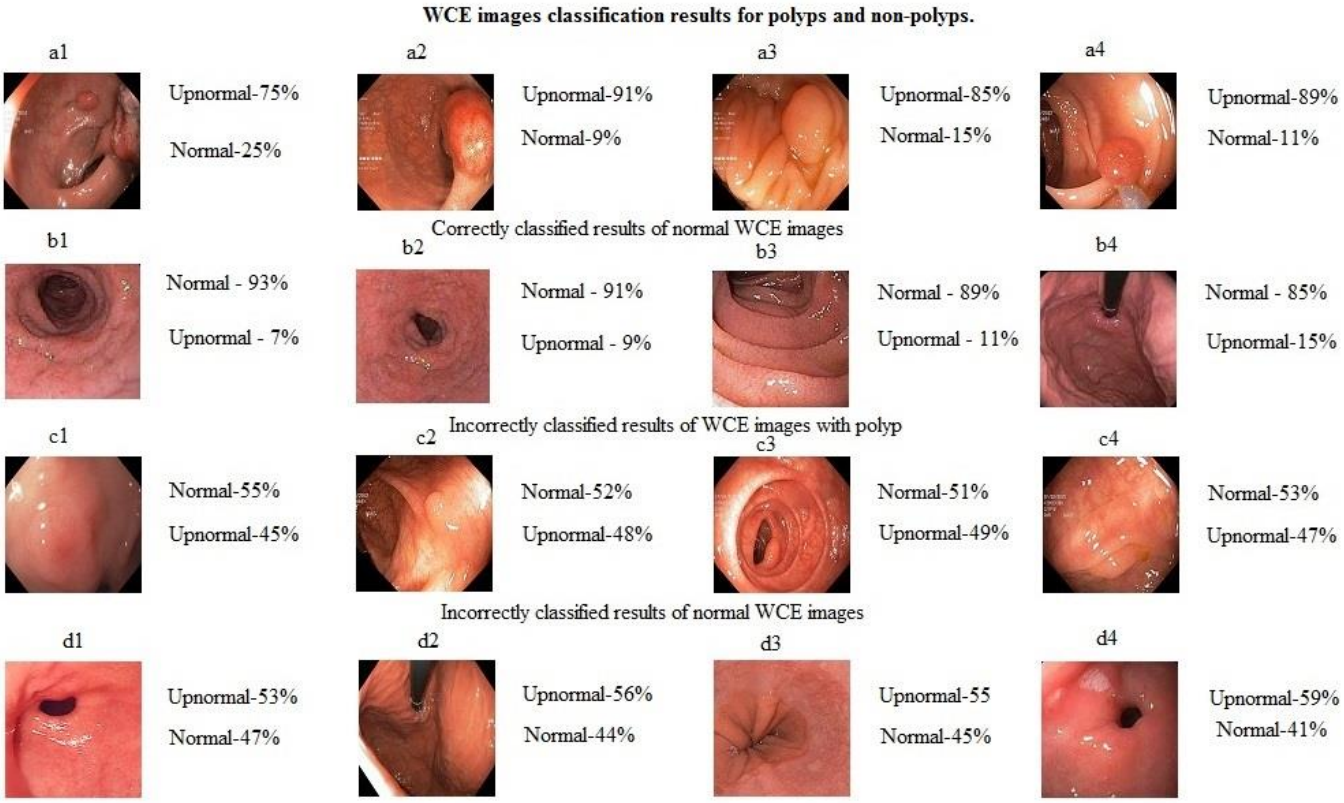


**Fig. 9. Some examples of cases classified correctly and incorrectly using CFL-CNN for both polyp and non-polyp classes**.

## V CONCLUSION

Accuracy is paramount in medical research. Even a small misclassification can have far-reaching consequences. The proposed research develops a method for detecting different types of gastrointestinal tract polyps. The GI tract's structure is similar to the shape, color, and texture of some GI polyps. Thus, the probability of a high false-positive rate is extremely high. In this proposed study, a combined feature learning method for efficient polyp detection has been developed. This enables the effective integration of high-level and low-level WCE image features. As a result, the FP rate is reduced to a certain degree. The efficiency of the suggested CFL-CNN approach has been demonstrated experimentally. The proposed approach achieves an accuracy of greater than 95%.

In future research, more accurate and efficient methods for detecting bleeding, ulcer, and cancer in the GI tract should be developed.

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