International Journal of Current Bio-Medical Engineering (IJCBE)
Volume 4, Issue 1, January – February (2026)

RESEARCH ARTICLE

COPN-NET: DEEP LEARNING BASED COLORECTAL POLYP CLASSIFICATION VIA MOBILEREGNET AND DEEP BELIEF NETWORK

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Abstract – Colorectal polyp classification (CPC) is essential for the early diagnosis and prevention of colorectal cancer (CC). However, existing methods often struggle to accurately classify polyps due to variations in size, shape, texture, illuminations and imaging artifacts in colonoscopy images. To address these challenges, a novel deep learning based COPN-NET is proposed for CPC. First, the input colonoscopy images are denoised to remove image noise and retain the crucial structural information while preserving the boundaries of the polyps using an Adaptive Wiener Star Filter (AWSF). To enhance the diversity of the data set and the model's ability to generalize, data augmentation methods are used like flipping, rotating, scaling, or adjusting the brightness of the data. The improved images then fed into the lightweight feature extraction ability of MobileNet and the powerful representation learning ability of RegNet together to form a MobileRegNet architecture. The extracted deep features are fed to a Deep Belief Network (DBN) for classification into Normal, Adenoma, and Cancer. The proposed framework enhances the feature representation and classification results. Experimental results show that COPN-NET is able to obtain an accuracy (AC) of 99.08%, precision (PR) of 96.64%, recall (RE) of 95.71%, F1-score (F1) of 96.17%, and specificity (SP) of 95.61%.

Keywords *– Colorectal Polyp Classification, Colonoscopy Images, Adaptive Wiener Star Filter, MobileRegNet, Deep Belief Network.*

1. INTRODUCTION

The detection and prevention of CRC is of considerable importance as it is one of the most prevalent and lethal cancers in the world [1,2]. The interior lining of the colon or rectum can develop abnormal tissue growths called colorectal polyps, which are believed to be a precursor to CC [3]. Early detection and removal of these polyps can help to minimize the likelihood that a cancer will develop [4]. The most commonly used test to detect colorectal polyps is colonoscopy. But, the manual analysis of colonoscopy images is very time-consuming and relies on the skill of clinicians [5]. Thus, the development of automatic and accurate polyp detection system becomes an important area of research in medical image analysis [6]. Over the last few years, deep learning (DL) based approaches have demonstrated excellent performance in the task of CPC. Extracting discriminative features from colonoscopy images have been widely used using CNN like ResNet, VGGNet, DenseNet and EfficientNet [7,8]. Additionally, recently developed object detection techniques like YOLO, Faster R-CNN, SSD and Mask R-CNN have enhanced the localization and segmentation of polyps to a high level of AC.

Transformer architecture and CNN-Transformer fusion model have also been recently proposed to learn local and global features in medical images [9]. These strategies have shown to yield substantial increases in detection performance and have helped clinicians to diagnose patients in real-time during colonoscopy procedures [10]. Although the current DL approaches show good results, there are still some drawbacks. Variations in size, shape, texture and illumination conditions often make it difficult to detect small, flat and low-contrast polyps by many models [11]. AC detection may be impacted by artifacts such as blur, reflections, and occlusions. Additionally, most models require a large amount of processing power and annotation data for both training and use. Another major problem is extrapolating the findings to different clinical settings and imaging modalities [12]. These shortcomings demonstrate the need for more reliable, efficient, and accurate DL frameworks for CPC in real-world healthcare settings. In this study, an COPN-NET is proposed for automated CPC. The following is a summary of this work's main contributions:

- The input colonoscopy images are denoised by an AWSF that effectively removes noise while preserving important image details such as polyp boundaries, texture patterns and structural information required for accurate diagnosis.
- To boost dataset variety, reduce overfitting, and enhance the suggested model's capacity for generalization, the preprocessed images are enhanced using methods including rotation, flipping, scaling, and brightness adjustment.
- The improved images are fed into the MobileRegNet architecture, where RegNet learns rich hierarchical feature representations for efficient CPC while MobileNet carries out lightweight feature extraction.
- A DBN receives the derived deep features and uses them to robustly classify colonoscopy pictures into three groups.

The remainder of the paper is organized as follows: Section 2 presents the literature survey, Section 3 describes the COPN-NET, Section 4 discusses the experimental results and comparative analysis, and Section 5 concludes the paper with future research directions.

2. LITERATURE SURVEY

Several studies have looked into the CPC using DL and ML techniques in recent years. A review of a few recent research papers is given in the section that follows.

In 2024 Lalinia, M. and Sahafi, A., [13] suggested a CPC framework based on the YOLOv8 network. To increase detection robustness, a pooled dataset gathered from many public colonoscopy databases was used to train the suggested model. Numerous tests showed how well YOLOv8 identified polyps of various sizes and forms. During colonoscopy procedures, the model maintained real-time processing capabilities while achieving high detection AC.

In 2024 Wang, S., et al., [14] suggested a CPC model with YOLO and super-resolution reconstruction. Prior to polyp detection, the methodology improved image quality using super-resolution techniques. This method enhanced detection performance and made tiny polyps more visible. When compared to traditional YOLO-based techniques, experimental results demonstrated higher AC.

In 2025 Vazquez, F., et al., [15] suggested a YOLOv8 system for CPC that is based on transfer learning. Effect of Different Pre-training Data Sets on Detection was investigated. Model generalization was much enhanced by transfer learning, which also decreased training needs. This suggested method showed the best AC in detection compared to models trained from scratch.

In 2025 Gelu-Simeon et al., [16] suggested a DL based RTPoDeMo. Using the framework with an architecture adapted from YOLACT, colorectal polyps were also detected and segmented concurrently. Its efficacy in real-time clinical settings was validated by experimental assessments. The model was useful in improving the AC of delineation during the endoscopy procedure.

In 2025 Redjimi, K., et al., [17] suggested a YOLOv8-based real-time CPC system. The objective of the proposed framework was to rapidly detect the polyps in colonoscopy images with high AC. To enhance localization performance and decrease missed detections, sophisticated DL algorithms were used. High PR and appropriateness for computer-aided diagnosis systems were shown by the results.

In 2025 Zare, O. et al., [18] introduced an efficient CPC model LightAttn-YOLO-V8, it is a lightweight attention mechanism method. The proposed architecture enhanced feature extraction by incorporating attention modules into YOLOv8. The model was also designed for real-time deployment, ensuring computing economy and improving detection AC. The experimental results showed that the performance of YOLOv8 was improved when linked to the ordinary YOLOv8.

In 2025 Behzadi S., et al., [19] introduced a high-performance and lightweight real-time CPC framework by utilizing YOLOv11n and LOF for preprocessing. The method employed was the YOLOv11n network for the recognition of objects and the Local Outlier Factor (LOF) filter for the removal of noisy samples. The system achieved good detection AC and generalization ability on various datasets, the PR were 95.83%, and the mAP at 0.5 was 96.48%.

In colonoscopy images, the various categories of polyps may be confused with each other because of the different sizes, shapes, textures, illumination, occlusions and imaging artifacts of the polyps. These restrictions will impact the AC and reliability of computer-aided CC screening systems. To address these challenges, a new COPN-NET is suggested for CPC.

3. PROPOSED METHODOLOGY

In this study, an COPN-NET is proposed for automated CPC. Figure 1 shows the COPN-NET methodology.

3.1 Dataset description

Colonoscopy images gathered from the publicly accessible medical image archives Kvasir-SEG make up the CPC dataset. The dataset contains images of varying sizes, shapes, colors, and lighting conditions of polyp. The medical experts are provided with segmentation masks or bounding boxes to precisely locate the areas of interest in each image. The medical experts have segmentation masks or bounding boxes that they use to precisely identify the areas of interest (polyp regions) in each picture. Robust model training and evaluation are made possible by the dataset's inclusion of both normal and abnormal colonoscopy images. Data augmentation procedures namely rotation, flipping, scaling and brightness adjustment are employed to increase the diversity of the datasets. The photos are preprocessed before they are input to the DL model, such as scaling and normalization. For creating and verifying automated CPC systems, this dataset offers a thorough benchmark.

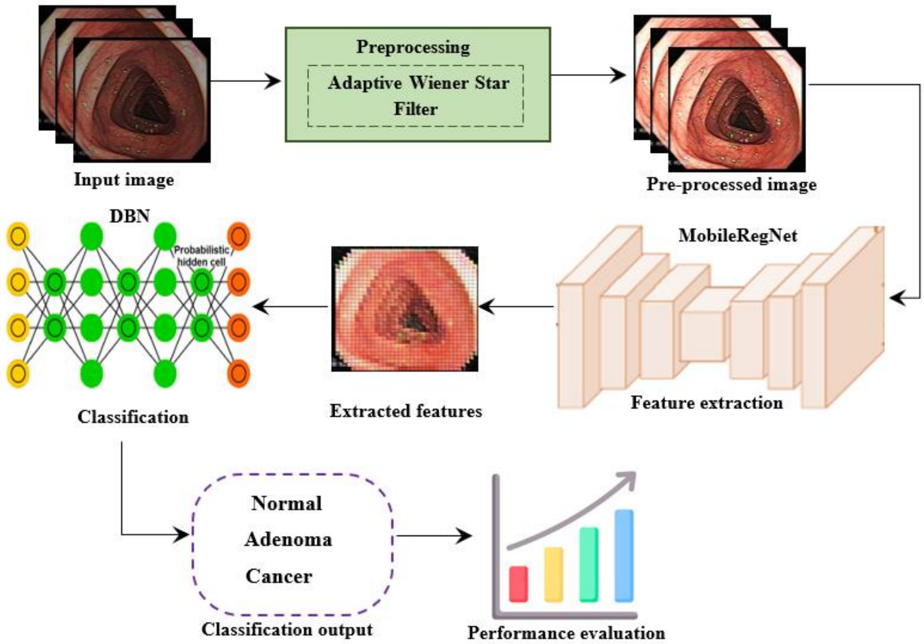


Figure 1: Proposed COPN-NET methodology

3.2 Pre-processing

In the study, an AWSF is used to extract the unwanted noise in the image and focus on the significant features of the image such as its edges, textures, or structural information of colorectal polyps. The AWSF is a local adaptive filtering technique with mean and variance of neighbouring pixels to enhance statistical images. The adaptive Wiener filter adapts itself to the local image properties, while smoothing filters may be able to smooth out important information in the image. The smoothness of the areas of high variation is preserved and the smoothness of the areas of low variation is lowered. This adaptation enables them to deliver effective noise reduction without compromising vital diagnostic data needed for accurate poly detection. In the filtering process, an approximation of original image is made to minimize the mean square error between the restored image and the observed noisy image. The Wiener filter solution is:

$$f(x,y) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}[g(x,y) - \mu] \quad (1)$$

It is a local mean intensity, σ^2 a local variance, $v^2$the noise variance, and (x,y) the restored image, $g(x,y)$ the input image of the colonoscopy. The filter is superior in enhancement performance compared with conventional linear filtering methods, because the filter adapts to the local picture statistics. To determine the local mean of the image, the following process is used:

$$\mu = \frac{1}{N}\sum_{(i,j)\in W} g(i,j) \quad (2)$$

In the same way, the local variance is calculated with:

$$\sigma^2 = \frac{1}{N}\sum_{(i,j)\in \mathrm{W}}[g(i,j) - \mu)^2 \quad (3)$$

The star filtering mechanism is applied after noise suppression to accentuate local structures and to better represent the polyp boundaries. Contrast is enhanced between the polyp and the surrounding mucosal areas, which aids in the extraction of features in later stages of the process. In addition, the image normalization is done to normalize the intensity value of the pixel and eliminate the illumination difference between the images of colonoscopy. The better images show sharper patterns and edges as well as lower background interference.

3.3 Feature extraction

For colorectal polyp detection, a novel hybrid DL architecture MobileRegNet is used. In this work, we fuse the light-weight feature extraction capability of MobileNet with the power of representation learning capability of RegNet, resulting in a new model named MobileRegNet. MobileNet adopts depthwise separable convolutions to greatly minimize the computation complexity and the size of the model, which is suitable for the efficient medical image analysis process. RegNet is a systematic framework for designing a network that yields optimized network structure for better feature learning and generalization performance. The combination of these two architectures yields high detection AC with low computational overhead, so that MobileRegNet has a great potential to be deployed in real-time applications. The MobileRegNet is composed of three main sections: the Stem, the Feature Extraction Body and the Classification Head. The stem is given the preprocessed colonoscopy data that extracts basic features with a conventional convolution layer, followed by Batch Normalization (BN) and ReLU activation. These extracted feature maps are fed to the MobileNet blocks, which effectively learn local texture and edge information pertinent to colorectal polyps by using depthwise and pointwise convolutions. Such operations can be light-weighted to decrease the number of trainable parameters and retain significant features of the image. The

MobileNet feature maps are then passed to the RegNet blocks. The RegNet component consists of multiple steps that are sequentially performed to gradually learn the high-level semantic features. The grouped convolution layer, the bottleneck layer, the batch normalization layer and the residual connection are all part of the stages. The residual learning mechanism can make the deeper network learning without degradation and it can also realize the efficient gradient propagation. Moreover, the width of the features changes dynamically stage-wise, enabling RegNet to learn fine-grained and global contextual information in colonoscopy images. The last classification head consists of Global Average Pooling (GAP) layer, fully connected (FC) layers, and a Softmax activation function. The GAP layer shrinks spatial dimensions, but retains key feature data. The FC layer is responsible for feature classification and the Softmax function predicts the probability of polyp presence in the input image. This hybrid architecture of MobileRegNet is able to optimize the computational efficiency and the detection performance, thus making it suitable for real-time CPC applications. The feature extraction process is shown as:

$$F_M = MobileNet(I) \tag{4}$$

where I denote the input colonoscopy image and FM represents the features extracted by MobileNet. The RegNet feature enhancement process is given by:

$$R = RegNet(F_M) \tag{5}$$

where R denotes the enhanced feature representation obtained from RegNet. The Global Average Pooling operation is expressed as:

$$G = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} R(i,j) \tag{6}$$

where H and W signify the height and width of the feature map. The final classification output is computed as:

$$Z = wG + b \tag{7}$$

where w represents the weight matrix and b denotes the bias term. The Softmax activation function predicts the probability of each class as:

$$P(c) = \frac{e^{z_c}}{\sum_{k=1}^{C} e^{z_k}} \tag{8}$$

where P represents the predicted class probability, w denotes the weight matrix, and b signifies the bias term.

3.4 Classification

After feature extraction, the extracted deep features are fed into a DBN for multi-class classification. The objective of the DBN classifier is to categorize the input colonoscopy images into three distinct classes: Normal, Adenoma and Cancer. For early identification and efficient clinical decision-making, colorectal anomalies must be accurately classified. The DBN can learn intricate associations between various colorectal tissue classifications thanks to the extensive spatial and semantic information included in the retrieved features. The DBN was created with a two-step learning procedure in mind. In order to minimize the difference among the original data and the reproduced data generated by the DBN, systematic modifications needed to be made.

$$D(u,l) = \frac{1}{Y} \exp\left(-A(u,l)\right) \tag{9}$$

$$P(w) = \sum_f \left(p\left(\frac{f}{U}\right) p\left(\frac{w}{f}, U\right)\right) \tag{10}$$

The vector used to join the DBN's total hidden layers $sum(z_d)$ should resemble this:

$$sum(z_d) = \sum_{c_j=1}^{m} num(fdc_j) \tag{11}$$

Using the weight and bias of the images to display the output of the hidden or invisible layer in equation (9).

$$A^d = \left[\sum_{m=1}^{l} Z_{md}^{G^t} * p_m\right] A_d \forall p_m = e_m^2 \tag{12}$$

The multilayered classification process's RBM layer output is represented by p_m, where A^d represents the data's hidden layer bias.

4. RESULT AND CONCLUSION

The A server with an Intel Xeon F8 CPU operating at 3.5 GHz, 64 GB of RAM, and an NVIDIA GPU with an 11 GB graphics card powers the COPN-NET, which is developed using MATLAB (2020b).

Figure 2 shows the COPN-NET simulation results using several image samples. The pre-processed images are shown in column 2, while the apple images are shown in column 1. The augmented images are shown in Column 3. Lastly, the detection output is displayed in Column 4.

4.1 Performance analysis

The evaluation of the COPN-NET including AC, PR, SP, RE, and F1 are utilized to determine the efficiency of the COPN-NET for detecting colorectal polyp.

$$SP = \frac{T_{neg}}{T_{neg} + F_{pos}} \tag{13}$$

$$PR = \frac{T_{pos}}{T_{pos} + F_{pos}} \tag{14}$$

$$RE = \frac{T_{pos}}{T_{pos} + F_{neg}} \tag{15}$$

$$AC = \frac{T_{pos} + T_{neg}}{Total\ no.of\ samples} \tag{16}$$

$$F1 = 2\left(\frac{PR+RE}{PR+RE}\right) \tag{17}$$

Whereas F_{neg} and F_{pos} indicate false negatives and false positives of the sample images, T_{neg} and T_{pos} indicate true negatives and true positives of the sample images.

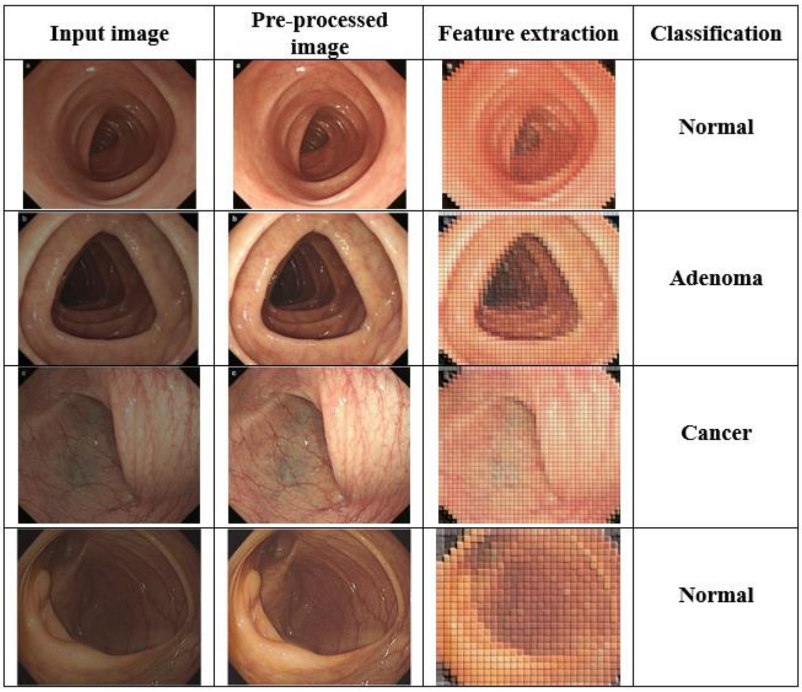
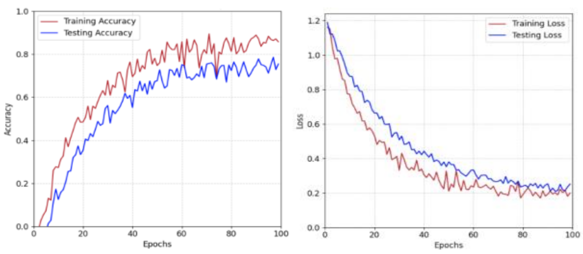


Figure 2: Experimental result of the COPN-NET

Table.1: Performance assessment of the COPN-NET

Classes	AC (%)	PR (%)	RE (%)	F1 (%)	SP (%)
Normal	99.12	96.84	95.73	96.28	95.92
Adenoma	98.76	95.67	94.81	95.24	94.56
Cancer	99.35	97.42	96.58	96.99	96.34
Overall	**99.08**	**96.64**	**95.71**	**96.17**	**95.61**

Table 1 presents the performance evaluation of the COPN-NET for classifying colonoscopy images. The model achieved an overall AC of 99.08%, demonstrating its effectiveness in CPC. The proposed framework attained 96.64% PR, 95.71% RE, 96.17% F1, and 95.61% SP. Among all classes, the Cancer category achieved the highest classification performance. These results confirm the robustness and reliability of the COPN-NET for accurate colorectal disease diagnosis.



(a) (b)

Figure 3: a) Accuracy and b) loss graph of the COPN-NET

Figure 3a) and b) show the COPN-NET accuracy and loss graph. Figure 3 a) defines the AC curve, with epochs and AC on opposing axes. As the number of epochs increases, the AC of the COPN-NET increases. The model's loss lowers as the number of epochs increases, as seen in Figure 3b) s epoch versus loss curve. The COPN-NET achieves an AC of 99.08%.

4.2 Comparative analysis

A comparison of the COPN-NET with other DL models is presented in this section. In order to demonstrate that COPN-NET outcomes are more successful, the efficacy of current methods using SP, PR, F1, AC, and RE was compared.

Table 2: Evaluation of the suggested method in comparison to current methods

Techniques	AC (%)	PR (%)	RE (%)	F1 (%)	SP (%)
CNN	90.84	87.52	85.61	86.54	85.38
ResNet50	93.17	89.84	88.76	89.30	88.15
DenseNet121	95.42	91.63	90.87	91.24	89.76
RegNet	97.18	93.25	92.41	92.83	91.28
MobileRegNet (Ours)	**99.08**	**96.64**	**95.71**	**96.17**	**95.61**

The performance of the DL techniques for CPC method is compared with the MobileRegNet in Table 2. From the results, it can be seen that the proposed model gives the highest AC of 99.08%, which is better than CNN model, ResNet50 model, DenseNet121 model, and RegNet model. It also attains superior PR (96.64%), RE (95.71%), F1 (96.17%), and SP (95.61%). Efficient feature extraction with MobileRegNet is used to achieve the enhanced performance. Thus, the proposed MobileRegNet-DBN framework can accurately and reliably classify Normal, Adenoma and Cancer colorectal images more than the existing methods.

Table 3: Comparison of AC among Existing Methods and the YOLOv13

Author	Approaches	AC
Lalinia, M. and Sahafi, A.	YOLOv8	94.80%
Wang, S., et al.	Super-Resolution + YOLO	95.60%
Vazquez, F., et al.	Transfer Learning YOLOv8	96.40%
Proposed	**COPN-NET**	**99.08%**

A comparison of the AC of the COPN-NET with existing CPC is given in Table 3. The COPN-NET achieved an AC of 99.08% which outperforms the available methods: YOLOv8, Super-Resolution + YOLO, Transfer Learning YOLOv8 and traditional YOLOv8 approaches. The results show that the COPN-NET is more accurate about the CPS than the existing techniques.

5. CONCLUSION

This research proposed a novel DL-based COPN-NET for CPC. To enhance important structural and texture information related to colorectal abnormalities and remove noise from input colonoscopy images, the AWSF is applied to preprocess the images. The improved images are input into the MobileRegNet to extract discriminative deep features and then classified by the DBN into three classes. The proposed system is capable of optimizing the feature extraction, classification, and diagnosis of leading using an integrated framework, which improves the diagnostic performance. COPN-NET achieves an overall AC of 99.08%, PR of 96.64%, RE of 95.71%, F1 of 96.17%, and SP of 95.61%. The experimental results demonstrate that the COPN-NET provides accurate and reliable CPC for supporting early CC diagnosis and clinical decision-making. In future work, the framework can be extended to incorporate polyp segmentation, multi-class disease grading, and real-time deployment in computer-aided colonoscopy systems for enhanced clinical applications.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING STATEMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to the supervisor and faculty members for their valuable guidance and continuous support throughout this research work.

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Arrived: 05. 01. 2026
Accepted: 10. 02. 2026