AUTOMATED COLORECTAL CANCER CLASSIFICATION USING RESIDUAL NEURAL NETWORK VARIANTS

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DOI: doi.org/10.34293/shanlax.9789361631474.ch008

Abstract

Colorectal cancer (CRC) is one of the deadliest cancer formed due to the abnormal growth of colon or rectum cells in humans. Our work presents a deep learning–based image classification approach for CRC diagnosis using two different Residual Network (ResNet) architectures. Residual Network (ResNet) architectures offer several significant advantages that make them highly effective for deep learning–based image classification tasks. In this work, ResNet-34 and ResNet-50 models were trained using colon gland image datasets to classify colorectal cancer cases into benign and malignant categories. Three distinct testing proportions—20%, 25%, and 40% of the entire dataset—were used to assess the performance of the suggested models. According to experimental results, ResNet-50 consistently achieves better accuracy, sensitivity, and specificity than ResNet-34 in all evaluation scenarios. These findings indicate that the proposed deep learning framework delivers robust, reliable, and reproducible results, highlighting its effectiveness for CRC diagnosis.

Keywords: *colorectal, image classification, deep learning, Convolutional Neural Network(CNN).*

1. Introduction

Colorectal refers to the colon and rectum parts of the large intestine. Colorectal cancer is a major global health concern, ranking as the second most common cancer in women and third in men. In 2020, there were nearly 1.9 million people affected with CRC. CRC is thought to be the second most common cause of cancer-related deaths, accounting for over 935,000 cases [1]. CRC are primarily classified as Adenocarcinoma, Carcinoid Tumors, Gastrointestinal Stromal Tumors, Lymphoma and Sarcomas. Early detection of colorectal cancer significantly improves patient survival and treatment outcomes. Methods for diagnosis of CRC include Colonoscopy, flexible Sigmoidoscopy, Fecal Occult Blood Test and Stool DNA test, Imaging Techniques such as CT colonography, Magnetic Resonance Imaging, Ultrasound and Histopathological Examination.

Treatment for CRC depends on the patient's condition, place of the tumor, and disease stage. The main course of treatment for colorectal cancer in its early stages is surgical resection.

Chemotherapy is used as a neoadjuvant or adjuvant treatment to slow the progression of the disease and lessen recurrence. In cases of rectal cancer, radiation therapy is primarily used to achieve local tumor control. To increase treatment accuracy, targeted therapy concentrates on particular biological processes. Immunotherapy is useful for some subtypes of colorectal cancer and strengthens the immune response. A multidisciplinary treatment approach improves overall patient outcomes.

Compared to traditional machine learning approaches, deep learning models automatically learn more discriminative and robust features, leading to improved image classification performance [2]. CNN is a popularly used deep learning model because of its better performance. In CNN, image features are extracted hierarchically through successive convolution layers, and the depth of the network significantly influences feature quality. Increasing CNN layers enables the extraction of finer and more detailed features, but may result in overfitting. Conversely, shallow networks tend to learn coarse features, which can reduce classification accuracy. By increasing the number of layers in the CNN model after numerous iterations and data training, the most useful feature information can be collected.Therefore, an appropriate network depth is essential to balance feature representation and generalization performance [3].ResNet-34 architecture after training around 40 epochs results in convergence [4].ResNet-34 model is the one which provides high accuracy [5]. ResNet50 architecture uses skip connections to solve the vanishing gradient issue and make it easier to train deeper networks [6].

2. Material and Methods

2.1. *Dataset*

The CRC pictures used in this investigation are taken from the Warwick-QU dataset, There are 74 benign and 91 malignant colorectal tumor samples among the 165 histological pictures in the dataset.. The spatial resolutions of the image files vary from 567 × 430 pixels to 775 × 522 pixels, and their sizes range from roughly 716 kB to 1.187 MB.

2.2. *Methodology*

The input image is acquired from the dataset and undergoes preprocessing before analysis. During preprocessing the image is converted to grayscale to enhance feature representation, followed by the application of Contrast-Limited Adaptive Histogram Equalization (CLAHE) to improve contrast Uniformity [7]. ResNet, introduced by He et al. in 2016 [8], is a deep learning architecture that employs residual connections, making deep network easier to optimize while achieving higher accuracy compared to earlier models [9].

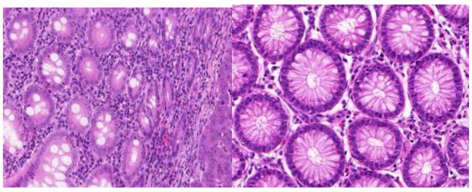

Fig. 1. Sample Dataset images.

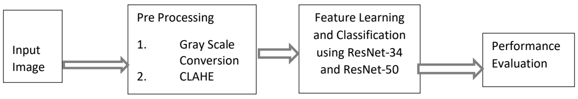

Fig. 2. Block diagram of proposed work

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		[3×3, 64; 3×3, 64] ×2	[3×3, 64; 3×3, 64] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3
conv3_x	28×28	[3×3, 128; 3×3, 128] ×2	[3×3, 128; 3×3, 128] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×8
conv4_x	14×14	[3×3, 256; 3×3, 256] ×2	[3×3, 256; 3×3, 256] ×6	[1×1, 256; 3×3, 256; 1×1, 1024] ×6	[1×1, 256; 3×3, 256; 1×1, 1024] ×23	[1×1, 256; 3×3, 256; 1×1, 1024] ×36
conv5_x	7×7	[3×3, 512; 3×3, 512] ×2	[3×3, 512; 3×3, 512] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Fig 3 ResNet Architecture [10]

2.3. *Performance Evaluation*

The performance evaluation metrics for the experiment consist of accuracy, sensitivity, and specificity. The formulas for calculating accuracy, precision, and recall imply follows

$$Accuracy = \frac{\theta+\delta}{\theta + \delta + ф+\eta}$$

$$Sensitivity = \frac{\theta}{\theta+ф}$$

$$Specificity = \frac{\delta}{\delta+\eta}$$

where θ is the number of true positives, δ is the number of true negatives, η is the number of false positives, and ф is the number of false negatives.

3. Results and Discussion

Three models of training and testing data were used in this experiments.The first model uses training and test data in the ratio 60:40,the second model uses training and test data in the ratio 75:25 and the third model uses training and test data in the ratio 80:20.After image splitting preprocessing the input image is done where Grayscale conversion and CLAHE contrast enhancement are used.The original input image,gray scale image and contrast enhaced image using CLAHE are shown in Figure 4. Following the preprocessing phase, the ResNet model is used for learning and finally the performance metrics are evaluated.

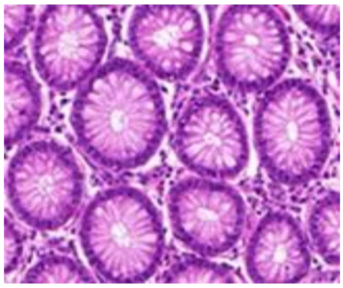

Fig a

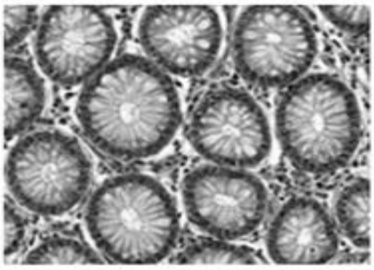

Fig b

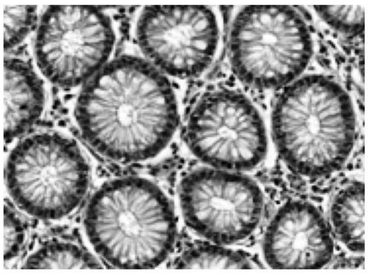

Fig c

Fig 4. a)input image b)gray scale image c)image after performing CLAHE

Table 1. Comparison of Accuracy, Sensitivity, Specificity value in several Testing Datasets for ResNet-34 and ResNet-50

Training Data: Test Data	Accuracy		Sensitivity		Specificity	
	ResNet-34	ResNet-50	ResNet-34	ResNet-50	ResNet-34	ResNet-50
60%:40%	76%	77%	67%	60%	86%	92%
75%:25%	84%	88%	98%/	89	66%	87%
80%:20%	88%	88%	86%	93%	90%	83%

Table 1, clearly shows that the efficacy of Resnet-50 is more than Resnet-34. The results of these estimations indicate that a model's ability to learn features improves with the number of stack convolution layers in the ResNet architecture. The data processing stage was performed on MATLAB tool version R2018a on an Intel Core i7 2.5 GHz with 16GB of RAM.

4. Conclusion

In this work three dataset distribution models are used to examine the Accuracy, Sensitivity, and Specificity values of two ResNet architectural models ResNet-34 and ResNet-50.ResNet-50 produces more accurate results than Resnet-34. Our investigation shows that the ResNet variations can diagnose colorectal cancer with accuracy around 88%,sensitivity around 93% and specificity around 83%. Colorectal cancer can be detected by the greatest classification model yet developed. We intend to use the associated datasets to include other architectures and their variations in the upcoming studies.

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