

# DEEP LEARNING FOR COLORECTAL CANCER DIAGNOSIS: A CLASSIFICATION APPROACH

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## **ABSTRACT:**

Cancer refers to a wide range of diseases marked by the unchecked growth and proliferation of irregular cells within the body. If not addressed, cancer can disrupt essential bodily functions and pose a serious risk to life. Colorectal cancer is one type of cancer. Colorectal cancer is one of the most common and fatal malignant neoplasms worldwide. Traditional diagnostic methods are based on histopathological analysis, which consumes time and affects inter-observer variation. Deep learning, in particular, convolutional neural networks (CNNs), has emerged as a powerful tool for automating and enhancing CRC classification. Conventional diagnostic techniques depend on histopathological assessment, which is time-consuming and susceptible to differences in interpretation among observers. Deep learning, especially convolutional neural networks (CNNs), has become an effective method for automating and improving the classification of colorectal cancer. This paper evaluates different deep learning strategies utilized for the diagnosis of colorectal cancer. The different architectures include GoogLeNet, AlexNet, VGG, Inception, ResNet. Out of most of the techniques available ResNet proved to be better among all.

**KEYWORDS:** Colorectal cancer, machine learning, deep learning, CNN, Alexnet, GoogleNet, VGG, Inception, ResNet.

## **1. Introduction**

The term "cancer" is used to refer to a broad category of diseases that can affect different body organs. These cells have the potential to develop into cancer as they divide and spread throughout the organs, which could result in death. Cancer ranks as one of the top causes of death, just behind cardiovascular diseases. Worldwide, colorectal cancer remains the third most commonly studied type of cancer and the third leading cause of deaths linked to cancer. The development of personalized medicine is a trending issue in cancer treatment, as it has the potential to enhance the effectiveness of therapy by tailoring it to the unique characteristics of each patient's cancer [1].

According to a National Cancer Institute (NIH) figure, there will be about 606,520 cancer-related deaths and 1,806,950 million new cases in the United States in 2020. The World Health Organization estimates that by 2040, 28.4 million new cases of cancer will be diagnosed worldwide, making it the leading cause of death worldwide [2]. Roughly 70% of cancer fatalities occur in low and middle-income nations. Merely 26% of nations with low income possess the necessary pathological materials required for cancer diagnosis accessible to the general public, based on data from 2016; affluent countries might provide cancer screening and

assessment to more than ninety percent of their populace [3-5].

Either the colon or the rectum is where colorectal cancer begins. Depending on where they begin, these cancers may also be referred to as rectal or colon cancer. Due to their many similarities, colon cancer and rectal cancer are frequently grouped together.

Colorectal cancer, commonly referred to as large intestine cancer (CRC) is the fourth leading cause of morbidity and the third primary cancer deaths globally [6].

Deep learning (DL), a branch of machine learning (ML), is frequently utilized in research fields, including medical image analysis, computer vision, speech recognition, and natural language understanding. Over the last six years, deep learning has garnered significant interest because of enhanced computing capabilities, decreased hardware expenses, and the development of numerous new datasets. Deep learning algorithms excel in identifying and diagnosing cancers, in addition to tumor segmentation, as they can directly extract advanced features from unprocessed images. Deep learning techniques can assist doctors by providing alternative insights and emphasizing regions associated with images [7].

## **2. Background Cancer**

One of the most critical illnesses is cancer. Human bodies are formed of cells. Cells are replaced by other freshly formed cells continuously. The cells are divided by cell division in which one cell is divided into smaller cells. All the information about a cell is stored in DNA in the form of genes. As the cell division takes place, the DNA and the information are passed to the newly formed cell. Mutation refers to mistakes that take place while passing the DNA further. Mutations are likely to happen while passing the information. The information stored in DNA instructs the cells about the time when it should stop the cell division. But the cell division does not stop if the cells are mutated, which causes the abnormal growth of cells. This abnormal growth of cells is called cancer.

This type of abnormal growth of cells can take place in any part of the body i.e. lungs, skin, brain, breast, colon, rectum, etc. When cells divide uncontrollably and form a cluster, a tumor results. However, since it is a benign tumor, treatment may not be necessary. A malignant tumor (cancer), on the other hand, is a type of tumor that spreads to other parts of the body and can have a variety of effects on your health [8]. Although there isn't a single way to avoid cancer, there are several variables that can lower your risk, including stopping smoking, getting vaccinated, getting regular checkups, keeping a healthy weight, exercising frequently, eating a healthy diet, and getting diagnosed early [9].

### **Colorectal Cancer**

Colorectal cancer refers to the abnormal growth of cells taking place in the colon or rectum. The colon or rectum are efficacious parts of the large intestine. This abnormal growth of cells in the large intestine results in inefficient working of the large intestine, i.e. it leads to problems related to the digestive system. Most of the functioning of body parts relies on the digestive system as it results in the extraction of nutrients. So, to safeguard the proper functioning of the digestive system, it is essential to detect colorectal cancer at an early stage [10,11].

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Deep learning (DL), a branch of machine learning (ML), is a device frequently utilized in research fields like healthcare image manipulation, machine vision, voice analysis, and processing of natural language. Over the last six years, profound learning has garnered significant interest because of the rise in processing capability alongside decreased hardware expenses and the development of numerous new datasets. Because deep learning algorithms can

directly extract high-level features from raw images, they are effective in tumor segmentation and cancer detection and diagnosis. By highlighting regions associated with images and providing secondary ideas, deep learning techniques can assist doctors. Additionally, among medical techniques, it has even been demonstrated that a single deep learning model is useful for diagnosis [7].

## **3. On-hand methodologies**

A convolutional neural network (CNN) is a form of deep learning method. Deep learning is a machine learning technique that employs artificial neural networks to learn from data. Deep learning can address numerous challenges, such as image identification, natural language understanding, and voice recognition. Deep learning models are capable of identifying data patterns, such as intricate images, written text, and audio. The names of the most well-known and widely used CNN architecture types in deep learning are AlexNet, GoogleNet, ResNet, LeNet, VGGNet, MobileNets, ZFNets, Inception, etc.

## **4. Literature Survey**

For the classification of colorectal polyps, multiple studies have been proposed, which are automated methods. For adenoma grading, two levels of classification are given, which are i) patch level classification and ii) whole slide image (WSI) level classification. But because of the high quality of histopathological images, inputting of whole slide into the classification model is impractical. However, downsizing WSI into smaller images can result in the loss of comprehensive information, which may be crucial for processing. Hence, the division of WSI into small patches and then performing two-level classifications is the most optimized way to solve the mentioned issue [12].

A study that looked into the use of DL algorithms for CRC detection was published in the literature. Sakr et al. [13], for example, provide an effective DL-based. The suggested technique extracts features from colon histology images using a deep convolutional neural network (CNN). A fully connected neural network is then fed the retrieved features to classify them. The research employed a dataset containing 1000 pathological images of colon cancer, which underwent preprocessing to eliminate background noise and improve image clarity. Following preprocessing, the images were augmented to expand the dataset and enhance the generalization capabilities of the model. A transfer learning method was applied to extract features from the preprocessed and augmented images, utilizing a pre-trained VGG-16 model.

Korbar et al. [14] created several deep-learning models to categorize five common types of polyps—hyperplastic, sessile serrated, traditional

serrated, tubular, and tubulovillous/villous—in light of the recent advancements in deep-learning techniques. Using a dataset of 2074 patches, they evaluated the performance of AlexNet, VGG, GoogLeNet, and a variant of ResNets. According to their tests, ResNetD fared better than the others and offered patch-level classification accuracy of 91.3%. Additionally, they evaluated their approach on 239 separate whole-slide H&E-stained images and obtained 93.0% overall performance accuracy, 89.7% precision, 88.3% recall, and 88.8% F1 score.

Nuclei detection and classification are the different histological image analysis tasks that are essential to retrain the pre-trained model. Convolutional Neural Networks (CNNs) are widely used to achieve this target of pre-trained model. They employed two distinct approaches to retrain the pre-trained model to arrive at the final results, which are the K-fold cross-validation method and the normal classification method. This model can classify the dataset in a variety of ways. To describe the Normal Classification Method (NCM), the dataset will be split into two sections, referred to as training data and validation data. So 70% of data for training and 30% for validation is chosen. Consequently, this model achieved excellent performance as it will be educated on the highest volume of information that may result in equipping a neural network with a robust ability to categorize colon cancer [15].

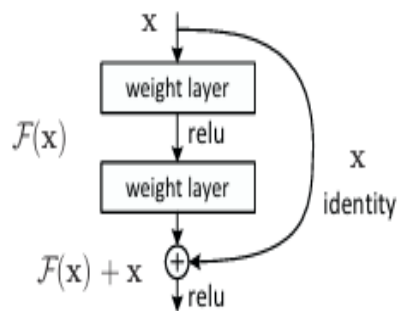
Additionally, Christian Szegedy [16] employed a somewhat better-quality, deeper, and wider Inception network; yet, its inclusion in the ensemble appeared to only significantly enhance the outcomes. They leave out the specifics of that network since empirical data indicate that the precise architectural characteristics have a negligible impact. Six of the seven models in our ensemble were trained using this network, which was trained using various image patch sampling techniques. Rectified linear activation is used in all convolutions, including those found in the Inception module. Our network's receptive field has a zero mean and measures 224x224 in the RGB color space. The numbers "#3x3 reduce" and "#5x5 reduce" indicate how many 1x1 filters were employed in the reduction layer before the 3x3 and 5x5 convolutions. Following the built-in max-pooling, the number of 1x1 filters in the projection layer is visible in the pool projection column. Rectified linear activation is also used by all of these reduction/projection layers.

Different CNN architectures are explained by Prashant Narayan Sholapur [17] for the effective detection of colon cancer. Out of many available methodologies, he focused on Inception V3 model. He retrieved information from [18], who said an artificial neural network with multiple layers is the Convolutional Neural Network model Inception V3. To determine whether colon cancer is present, the model is integrated with the collection of histological images. Convolutional layers, average

and maximum pooling, concatenation layers, fully linked layers, dropout layers, and SoftMax activation make up the Inception 3 model in our ensemble. Constructing the model is straightforward, with the installation performed automatically. The alteration of weights will occur when the model is built. For weights, the parameter is allocated. The ImageNet, which will enable the use of the weights that are pre-trained on ImageNet.

### 5. Proposed Methodology

There are various architectures available in deep learning techniques. In this paper, the classification of colorectal cancer is proposed using ResNet architecture. ResNet stands for Residual Network. A phenomenon known as the "vanishing gradient problem" happens when deep neural networks are being trained. The gradients that are used to update the network get so little or "vanish" as they are backpropagated from the output layers to the previous layers. To overcome this problem, a deep learning residual framework is used. ResNet specifically allows safe stacked layers to fit a residual mapping rather than relying on them to directly match a specified underlying mapping. With shortcut connections, feedforward neural networks can implement the formulation of  $F(x)+x$  [19]. Connections that skip one or more layers are known as shortcut connections [20,21]. In this instance, the shortcut connections merely carry out identity mapping, adding their output to the stacked layers' outputs.



Feedforward neural networks with "shortcut connections" can be used to achieve the formulation of  $F(x)+x$  (Figure 1). The outputs of the shortcut connections are simply added to the outputs of the stacked layers, and they carry out identity mapping (Figure 1). Identity shortcut links don't increase computational complexity or add unnecessary parameters.

## 6. Conclusion

The proposed model of classification of Colorectal cancer using deep learning techniques proposes the early detection of colorectal cancer and can be implemented best using Residual Network, i.e. ResNet. As ResNet can overcome the vanishing or disappearing gradient problem that can occur in any CNN architecture. Any biological or histopathological images i.e., any image related to medical imaging, are mostly asymmetric. So, for the processing of medical images, a very deep neural network is necessary. ResNet can learn more complex features because it can train very deep networks, which is the most important advantage of ResNet when it comes to medical images. ResNet's quality of reducing the vanishing gradient problem made it a winner in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The learning rate of ResNet is within the ideal range of learning rate, i.e. 0.001 to 0.01. Hence, it is one of the advantages of ResNet over other architectures that makes it better than other architectures. It is also observed that ResNet resulted in 93% accuracy for patch-level classification and about 93% accuracy in whole slide images, which is again a better result. Along with the accuracy, it also provides good precision, recall, and F1 score, which are significant parameters in Deep learning. The model's accuracy can be extended to 95%, which is an outstanding outcome. Hence, taking into consideration the overall study, I would like to summarize that ResNet architecture can give better results for the classification of colorectal cancer using deep learning techniques.

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