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A Comprehensive Review on Colon Cancer Detection using Deep Learning

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Abstract: Deep learning has emerged as a main machine learning tool in object detection and has attracted interest with its achievements in progressing clinical image evaluation. Convolution Neural Networks (CNNs) are the most preferred technique in deep learning algorithms for this reason and that they have a crucial role in the detection and capability in early analysis of colon cancer. In this paper, we are hoping to carry out a perspective to development on this region by reviewing deep learning practices for colon cancer analysis. This examines and gives an outline of popular deep learning architectures utilized in colon cancer evaluation. After that, all research associated with colon cancer analysis are accumulated below the sector of colon cancer and deep learning. We conclude our work with a summary of latest deep learning practices for colon cancer analysis, a crucial discussion of the challenges confronted, and recommendations for future research.

***IndexTerms* - Deep learning, Colon cancer, colorectal cancer, Convolution neural networks.**

Introduction

In recent times, most of the cancers is one of the primary diseases that has been affected human health and has a high rate of mortality. Cancers are the reason of malignant tumors. Benign tumors are not cancers and they may be frequently eliminated and might not often be risky, as they are regularly doing no longer recurs. Malignant tumors or cancers, however, are risky due to the fact they develop uncontrollably and irregularly. In all sorts of cancer, a few cells of the body begin to divide and start to spread round the encircling tissues. The statistics of the cancer Institute (NIH) in the country wide suggests that about 606,520 human beings will die and 1,806,950 million new incidences of cancer might be diagnosed in the America in 2020 [1].Most of the cancers, consequently, is a main task to health center and medical doctors and researchers who are inquisitive about this discipline.

Early diagnosis of cancer prolongs human lifestyles and is essential in preventing the disease [2]. It is truly why scientists have offered many research for the early detection of cancer [2]. Clinical imaging is a powerful utility used in the early analysis of cancer and performs a enormous role [3]. Despite of the growth in clinical imaging data, interpretation of the data in relation to the rate of progression of the disease is time consuming and difficult. Similarly, if physicians' misinterpretation of data is taken into consideration in the detection of diseases, the accuracy rate decreases sharply and the period of early detection is extended [4]. Machine learning, which is a sub branch of artificial intelligence, is broadly used in clinical image processing for cancer detection, category, and tumor segmentation analysis [5].

Moreover, in the mid-1960s, machine learning algorithms began to be used to analyze and interpret medical images, and this has continued to this day [6,7]. With these advances, computer-aided detection/diagnosis (CAD) algorithms were developed to give more accurate and effective results in the interpretation of medical imaging. Computer-aided detection/diagnosis (CAD) algorithms began to develop in the mid-1980s and were first used for chest radiography and mammography for cancer detection and diagnosis [8]. It was then extended to other methods such as computed tomography (CT) and ultrasound [9].

In the early days, CAD algorithms used a largely data-driven approach, as most deep learning algorithms do today. But their early CAD ways were predominantly based on feature extraction. Feature extraction did not help the development of CAD systems since it had a lot of weaknesses [10]. To cope with these weaknesses, feature extraction was replaced by representation learning and deep learning, a type of representative learning was utilized to improve the performance of the CAD systems [11].Deep learning (DL), a subfield of machine learning (ML), is a tool commonly used in research areas such as medical image processing, computer vision, speech analysis, and natural language processing. In the past six years, deep learning has attracted great attention due to the increase in computing power with the reduction of hardware costs, and the creation of a large number of new datasets. Deep learning algorithms are powerful in the detection and diagnosis of cancers, as well as tumor segmentation because it can extract high-level features directly from raw images.

Deep learning methods can help physicians by offering secondary ideas and highlighting areas related to images. Also, a single deep learning model has even been shown to be effective in diagnosis among medical methods [12]. Convolution neural networks (CNNs), a type of deep learning algorithm, have become central in the field of deep learning with success in the processing of medical images [10]. Since hardware requirements can be found easily in recent times, the area of deep learning have been the subject of many new studies and have enabled many new researchers to undertake new research. Moreover, firms such as Amazon, NVIDIA, and Google introduced cloud-based solutions for deep learning to train models remotely. All of these improvements have enabled deep learning methods to reach users more quickly.

Colon cancer or colorectal cancer (CRC) is a serious cancer type with high incidence and mortality rates in developed countries. Colorectal cancer (CRC) ranks third in the United States among cancers diagnosed in both men and women [13]. Colon cancer and rectal cancer are often grouped together because they have many common features. In this study, rectal, colorectal, and other types of cancers related to colon cancer were collected and analyzed under the title of colon cancer. The pre cursor of colon cancer is polyps that turn into cancerous cells over time. Colonoscopy is the most widely accepted standard for the detection of these polyps and colon cancer screening.

In section 2, a brief introduction to the main deep learning techniques used for colon cancer analysis is presented. However, our intention is not to provide comprehensive technical details of deep learning or its wider applications. In section 3, deep learning applications used in colon cancer are divided into five main categories; detection, classification, segmentation, and survival prediction. While these five categories contain a detailed summary of each article, they also include a particular table with the results of each article, the deep learning method, and their respective datasets. Section 4 discusses the obtained results and existing challenges such as datasets in different application areas. Finally, we conclude the review and summarize the proposals for improvements in section 5. We hope this article will be beneficial to researchers interested in studying colon cancer and deep learning.

2. Deep Learning Approaches

Deep learning is one of the most widely used tools of artificial intelligence, and it is a sub-branch of machine learning. Generally, deep learning is a method of automatically extracting useful features by arranging multiple linear and nonlinear processing units in a deep architecture [14]. The history of artificial neural networks, which form the basis of deep learning, dates back to the 1940s. The first artificial neural network was applied as a perceptron [15]. After this time, neural networks have developed, but not significantly. In the last 10 years, artificial neural networks have made rapid progress and the name of deep learning has started to be used. Depending on the type of application, many deep learning models are used. In the current study, deep learning architectures can be divided into three main classes: unsupervised deep networks, supervised deep networks, and hybrid deep networks. CNN and CNN 'derivatives,' a type of supervised learning, are the leading and most popular architectures in medical image processing [16–18]. Hybrid deep networks refer to structures that are designed to give better results by combining different deep learning architectures. This section aims to provide a general and formal presentation of the most widely used deep learning concepts and architectures in the studies we study. The most used and successful deep learning models in the colon cancers are CNN and its variants, auto encoders, and deep belief neural networks respectively.

Conventional ML approaches are largely based on predefined engineering features and are generally designed only for specific problems. However, DL algorithms do not require explicit feature definition; instead, they use data and combine high-dimensionally difficult to interpret features to achieve a result. Due to superior performance and success of deep learning algorithms, many algorithms such as random forest, support vector machines [SVM], and Gauss mixture models, which are among the classic machine learning algorithms, have been replaced by deep learning algorithms. These conventional methods are not robust, flexible and they are time-consuming as they are manually designed in colon cancer analysis. For instance, these methods are not successful in real-time polyp detection for colonoscopy images because of high false-positive rates. In some studies, there are generally studies consisting of texture features [19], position and color features [20], or a mixture of these features [21], and they are rather weak in performance compared to deep learning methods.

2.1 Convolution neural networks (CNNs)

Convolution neural networks (CNNs) are variants of the multi-layer perceptron and are biologically inspired by the work of Hubel in the visual cortex of a cat [22]. CNNs tend to recognize visual patterns directly from raw image pixels. The first proposed CNN model for recognizing handwritten characters (LeNet-5) is presented in [23]. A CNN can be defined as an artificial neural network that performs a mathematical operation called convolution instead of matrix multiplication in layers [24]. CNNs, the most widely used architecture of deep learning, are also the most researched and used machine learning algorithm in image analysis such as medical image processing and analysis [5].

The main reason for this is that CNNs receive and process input images and modify them, but spatial relationships are preserved. Spatial relations are a crucial point in medical image analysis since the relationships and interactions of cancerous tissue with normal tissue can be read through spatial relationships.CNNs are a deep learning architecture that has been proposed for solving image processing problems and can adapt to images quite well. In CNN architecture, layers are connected in various blocks instead of being directly connected. The information transfer between these blocks is similar to the visual cortex and eliminates the problems of classical techniques. Also, it can automatically learn features from the raw data, thus avoiding the difficulties of manual feature extraction. Since properties are shared in CNNs, the number of parameters is less than it should be. In this way, the network can enable faster learning, and over fitting problems are avoided. CNNs are data-hungry deep learning architectures and millions of parameters can be trained, so they perform well in medical image analysis. The fact that there are many similar advantages paves the way for the use of CNNs in many more areas.

2.2Other deep learning architectures

This section will give a brief overview of other popular deep learning architectures, unlike CNN architecture. These popular deep learning architectures are recurrent neural networks (RNNs), auto encoders (AEs), restricted Boltzmann machines (RBMs), and deep belief networks (DBNs), respectively, which are shown together in Fig. 1.

2.2.1 Recurrent neural networks (RNNs)

Recurrent neural networks (RNNs) are used more often than other deep learning methods in analyzing and coping with sequential data and they perform better. In particular, due to their ability to process text and produce text, RNNs have been used in text analysis such as speech recognition, text prediction, and machine translation. Depending on the nature of the ordered data, the parameters at different time intervals of the RNN model are shared. Normally, in flat RNNs, the output of one layer is added to the next entry and is fed back to that layer, resulting in a memory capacity problem. These temporal gradient problems make the training of networks difficult in practice and make it difficult to model temporal dependencies. As a remedy to this problem, LSTMs have been developed, and the problem of RNNs has been addressed by adding memory cells and various gates. In this way, short or long patterns in temporal data become learnable. RNNs are rarely used in medical image processing and are often applied in the form of hybrid models using CNNs or other deep learning models. These hybrid models are generally used in segmentation processes. A typical chart of RNNs is illustrated in Fig. 1 (b).

2.2.2 Autoencoders (AEs)

Autoencoders are an unsupervised deep learning method that learn properties from input data without labeled data. Autoencoders (AEs) consist of three layers: input, hidden, and output layers. Although the structure is similar to feed forward neural networks, the aim is to create a different representation of the input in the hidden layer. A typical chart of AEs is illustrated in Fig. 1 (c). AEs receive input data, collect codes from them, and then use these codes to regenerate output data. The basic logic is that the input data are as similar as possible to the input data. They, therefore, include a cost function that punishes the model when the inputs and outputs are different. AEs do not need training data to be labeled. Encodings are usually of a smaller size, which reduces computational complexity. Also, they produce output similar to input training data. With all these advantages, it is frequently used after CNN in medical data processing where labeled data is scarce.

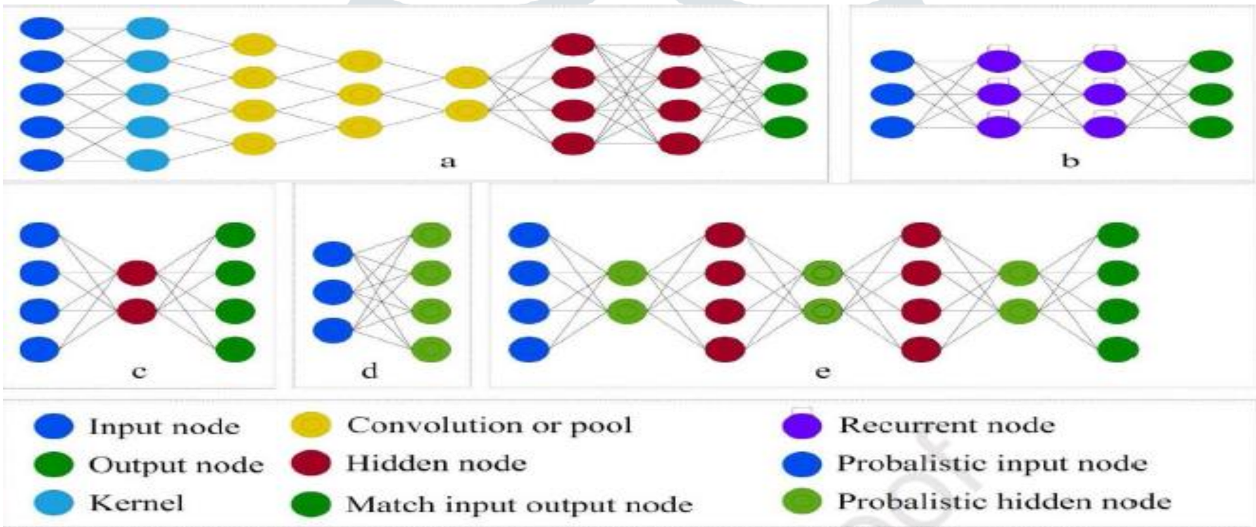

Fig. 1. Five deep learning architectures can be divided into two main categories: supervised learning algorithms including CNNs (a) and RNNs(b); and unsupervised learning algorithms including AEs (c), RBMs (d) and DBNs(e)

There are many types of AEs and the most commonly used ones are; Stacked Autoencoders, Denoising Auto encoder, Sparse Autoencoders and Variational Autoencoders.

2.2.3 Restricted Boltzmann machines (RBMs) and deep belief networks (DBNs)

Restricted Boltzmann Machines (RBM) [51] was first introduced in 1986, but later in 2006 was recognized by Geoffrey Hinton et al. as a rapid learning algorithm [52]. RBM is a variant of Boltzmann Machines and it is a productive random neural network that can learn the probability distribution on the input set. RBMs are two-part graphs with symmetrical connections between them, hidden and visible. RBMs are commonly used in areas such as feature learning, classification, and size reduction. A typical chart of RBMs and DBNs is illustrated in Fig. 1 (d) and Fig. 1 (e) respectively. Deep Belief Networks were proposed by Hinton et al., with an unsupervised greedy learning algorithm to create one layer at a time. The basic idea is to use an RBM network that models the output of the previous layer and to use this RBM network to train each layer of the network independently. Combining multiple and simpler RBM models with this process is an effective way to learn a different model. When a DBN is trained on an unsupervised sequential instance, it can learn the probabilistic reproduction of inputs. The layers of the DBN then act as a feature extractor. After learning in this way, a DBN can be further educated in a supervised manner to classify. A typical chart of main deep learning architectures is depicted in Fig. 1.

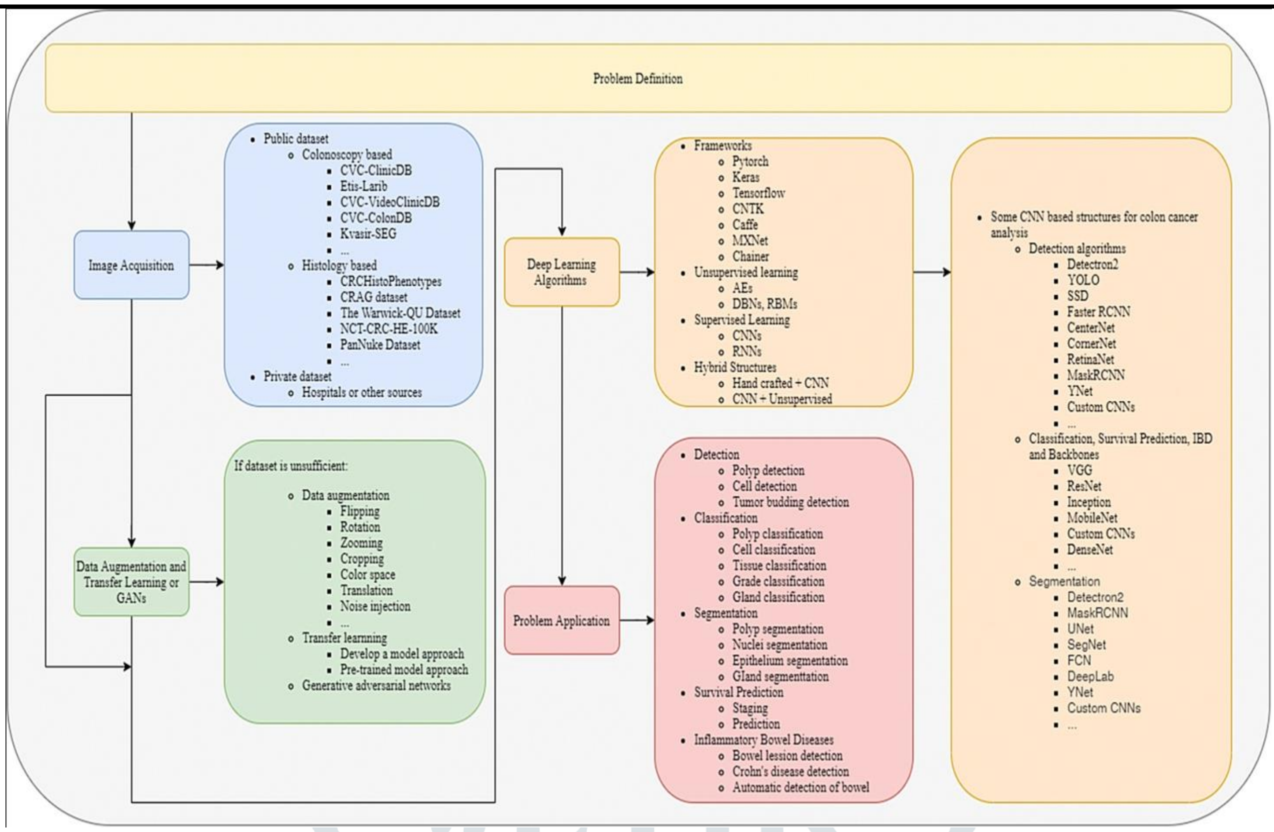

Fig. 2. Stages of applying deep learning techniques to colon cancer analysis.

3.Deep Learning Applications in Colon Cancer

To show better the success of deep learning in colon cancer analysis, we have divided the collected studies into five main categories.These categories are as follows: detection, classification, segmentation, survival prediction, and inflammatory bowel diseases.

4. Applying deep learning to colon cancer

In this section, the basic steps required for the successful implementation of deep learning methods will be briefly stated. Our aim here is to assist researchers who will use or apply deep learning architectures for the first time in colon cancer analysis. For this, the basic steps required for applying deep learning architectures in colon cancer analysis are shown in Fig. 2. The first step to implementing deep learning architecture is to identify the problem correctly. The problem might be a classification, detection segmentation problem, or another task. The next step is to have a sufficient input dataset for deep learning architectures. Data augmentation and/or transfer learning or GANs is often used when there is no sufficient dataset. Using these two methods, the amount of data is enlarged and the network can be trained on pre-trained weights. In the next step, in the case of labeled data, supervised learning algorithms are used, otherwise, unsupervised or hybrid learning algorithms are utilized. Most of the studies in colon cancer analysis use CNNs, one of the supervised learning algorithms. Then, one of the current sufficient CNN architectures is selected and training processes are started. At the last stage, the network is tested with a dataset that has not been seen before. Briefly, the application of a deep learning network to colon cancer consists of these stages.

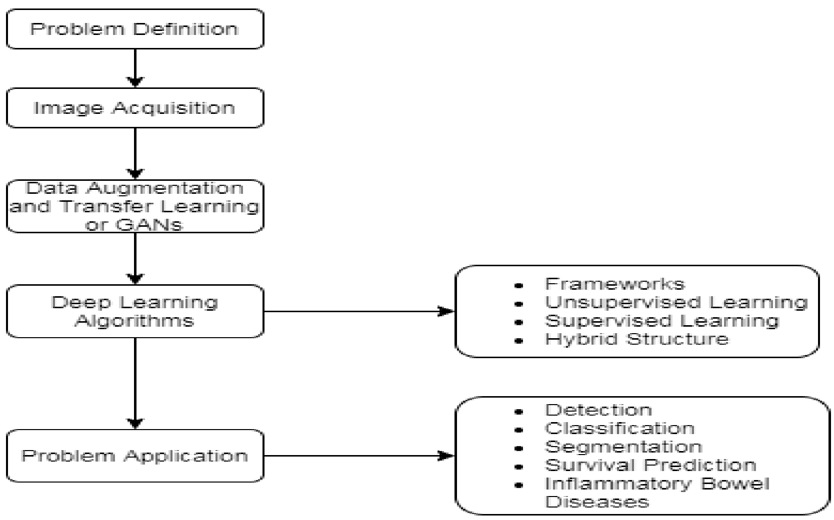

Fig. 3. Flow chart for applying deep learning techniques to colon cancer analysis.

Study	Task	Models	Framework	TL	Layers replaced	Output layer
Ribeiro et al. 2016[26]	Classification	AlexNet, GoogLeNet, Fast CNN, Medium CNN, Slow CNN, VGG16, VGG19	-	ImageNet	Layers after last CNN layer	SVM
Zhang R. et al. 2017[27]	Detection and classification	CaffeNet	-	ImageNet and Places205	Tested connecting classifier to each convolutional layer (5 convolutional layers)	SVM (Poly, Linear, RBF, and Tahn)
Chen et al. 2018[28]	Classification	Inception v3	-	ImageNet	Last layer	FCL
Misawa et al. 2018, Misawa et al. 2019[29]	Detection	C3D	-	N/A	N/A	N/A
Zheng Y. et al. 2018[30]	Localization	-	YOLOv1	PASCAL VOC 2007 and 2012	-	-
Shin Y. et al. 2018[31]	Localization	Inception ResNet-v2	Faster R-CNN with post-learning schemes	COCO	-	RPN and detector layers
Urban et al. 2018[32]	Localization	ResNet-50, VGG16, VGG19	-	ImageNet Also without TL	Last layer	FCL
Wang et al. 2018[33]	Localization	VGG16	SegNet	N/A	N/A	N/A
Wittenberg et al. 2019[34]	Localization	ResNet101	Mask R-CNN	COCO	Last layer	FCL

Table 1. Comparison between different types of deep learning technique

5. Discussion and Summary

Deep learning, a subfield of artificial intelligence, has become the center of attention especially with its achievements in areas such as healthcare, object detection, self-driving cars, speech recognition, natural language processing, marketing research, and image processing. Its potential to perform visual recognition competitive with humans, especially in the fields of health and medical imaging, makes it significant. With this success, deep learning has contributed greatly to assisting medical doctors. It has also been contributing to a quality increase in health systems. The advanced detection, segmentation, and classification capabilities of deep learning in medical imaging have made it even more powerful. Colon cancer image analysis is a sub-branch of medical image processing. Despite these achievements, deep learning faces some difficulties in medical image processing and colon cancer image analysis. In this section, some features such as the difficulties, the advantages, and the successes of deep learning in colon cancer analysis will be examined systematically.

6. Conclusion

Colon cancer ranks in the top three among the most severe and deadly cancers in the world. As with any cancer, early diagnosis is the most important stage. Deep learning applications have recently become very popular in medical image analysis due to the effects and successes it has achieved in early detection and screening of a cancerous tissue or organ. In this article, we have reviewed the latest studies on the application of deep learning methods used only in the detection and diagnosis of colon cancer. To make the review more comprehensible, we gathered all the works together and organized them into five main categories. These categories are listed as follows according to the number of studies conducted: detection, classification, segmentation, survival prediction, and inflammatory bowel diseases. We present the summaries of the studies in each category with different aspects. We also listed the works in tables to make a more detailed comparison. These tables are composed of different tables including datasets, imaging techniques, and results of each study. After expressing the successes of deep learning for colon cancer analysis, we also revealed the difficulties experienced. Finally, we made some suggestions such as increasing the number of public datasets and determining common experimental setup and evaluation criteria for future studies and researchers.

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