CNN,RNN and Transfer Learning for Colon Cancer Classification

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Abstract: Colon cancer is auncontrollable cancer, which also transfer across the world. It is also a leading cancer and considered as major killer among all kinds of cancers. In modern times, advances are developed in treatment field of this frequently causing disease. There are several techniques which are not flexible, robust and time consuming as they are devised for manual assessment of colon cancer. Hence, in this research deep learning techniques namely convolutional neural network (CNN), recurrent neural network (RNN), transfer learning. In this work, pre-processing is conducted utilizing median filter for removing noises from an input colon cancer image. The filtered image is then segmented using SegNet, which is utilized to segment the affected portions. Finally, classification of colon cancer is conducted employing various deep learning approaches like CNN, RNN, and transfer learning. The comparative assessment showed transfer learning as the best classifier for colon cancer classification with maximal values of accuracy as 88, sensitivity as 82 and specificity as 78 respectively for 60% training data .

Keywords:*Convolutional neural network (CNN), Recurrent neural network (RNN), transfer learning***.**

I. INTRODUCTION

Colon cancer is the third common kind of cancer across the globe. Colon cancer is frequently causes other than rectal cancer, which is commonly occurs in higher income countries but nowadays it is increasing in the middle as well as lower income countries [2].Cancer signifies to a categorization of illness wherein abnormal cells are developed inside human body as an outcome of random alterations [1]. The number of diverse staging condition is utilized for estimating deepness of cancer penetration in colon and extension of extracolonic disease participation. If no prediction is carried out in earlier detection, it causes serious problem to public health conditions [3]. Earlier identification of colon cancer is the significant objective for doctors to evaluate patients at danger. Colonoscopic regimens of observation have been emerged on basis of better evidence, which can improve mortality and morbidity [4].The number of guidance is established forendoscopic observation of high danger groups to identify colon cancer [5].When healthier cells and lining of colon or rectum expands in an uncontrollable manner, a cancer occurs. This kind of cancer is generally malignant [3] [6]. Adenocarcinoma of colon or rectum generally develops with large intestine lining, beginning in epithelial cells and spreads to other layers [6].

Even though, imaging techniques are vital in specifying suspected regions of involvement, entire stage presently needs pathological analysis of resected tissues, especially to define earlier stage of disease [5]. Additionally, upstaging of the colon cancer results from utilization of magnetic resonance imaging (MRI), position emission tomography, computed tomography (CT) [7], ultrasound with pathological confirmations [5]. In recent times, digital pathology is emerging as vital tool for prognosis and diagnosis of cancers [8] [9]. Hence, recent technology progression has been extremely contributed to digital pathology proliferation in diverse applications. Other than classical glass images, the new Whole Slide Images (WSI) are mathematical copies of stained samples [10]. These images plays a main part in a process of pathological diagnosis [11] [12] [13] because it enables easier data storing and sharing [9]. Presently, a novel intra-operative device utilizing confocal laser microscopy (CLM) is presented, which offers submicrometer image resolutions [14]. Nowadays, automated tissue classification has been addressed successfully utilizing deep learning techniques [15] like CNN for the semantic segmentation as well as classification [16] [17]. Deep learning enabled colon cancer diagnosis has been raising prominent probe theme in current years. On the other side, capsule networks are gaining recognition in medical imaging classification owing to its low weight systems [18] [19] [6].

The prime goal of this work is to perform comparative assessment of colon cancer classification using diverse deep learning approaches. Colon is the main constituent of large intestine and colon cancer is an important reason of death in many countries. Here, an input image is considered from specified dataset and given to pre-processing phase. The goal of pre-processing is the enhancement of an image.In pre-processing, the noises are eliminated from an input image utilizing median filter [20]. Thereafter, pre-processed image is given to segmentation stage wherein affected regions in an image are segmented utilizing SegNet [21]. Then, segmented output is passed to classification phase wherein colon cancer classification is carried out utilizing CNN [22],RNN [23], transfer learning [17], AlexNet [24]and GoogLeNet [25]. As deep learning has vast impact in regions like diagnosing of cancer and so on. Hence, comparative analysis is performed to reveal the best classifier for classification of colon cancer.

Achief contribution of this work is explicated beneath.

- **Assessment of various deep learning techniques for colon cancer classification:**Here, several deep learning techniques like CNN, RNN, transfer learning, AlexNetand GoogLeNet are compared to prove the efficacy of GoogLeNet for colon cancer classification.

The following sections are arranged in a manner as follows: Section 2 interprets literature overview and section 3 specifies methodology for comparative assessment. Section 4 elucidates comparative outcomes and section 5 concludes the assessment.

II. MOTIVATION

Colon cancer is the most general kind of cancer that directs to short period of survival. Therefore, deep learning approaches are required for instant assessment, which motivated this research to compare diverse deep learning techniques to identify the better classifier for colon cancer classification.

A.Literature Survey

The survey done utilizing the existing deep learning methods are interpreted as follows. Nils Gessert., *et al*., [22] utilized CNN to differentiate benign as well as malignant tissue and investigated the possibility of automated classification of colon cancer. This classifier showed detection of cancer from CLM images is possible employing CNN but did not utilize many data.LichaoMou., *et al*., [23] developed RNN method for classification of hyper-spectral images was proved as faster in the testing. Though, it needs more tolerable time for training as it generates extra channel updates. Nils Gessert., *et al*., [17] assessed the possibility of classification from CLM in colon employing transfer learning. The outcomes demonstrated that transfer learning is applicable for identification of cancer tissues with CLM but it has less features transferability.Rika Sustika., *et al*., [25] evaluated GoogLeNet for improving the performance, which showed rapid speed but it needs many resources for computation.

A. Major Challenges

The demerits faced by several classifiers reviewed for colon cancer classification is expounded below.

- CNN utilized in [22] for automated classification of colon cancer showed the feasibility to detect cancer, but still it failed to investigate malignant tissue detection in colon region.
- In [17], transfer learning was investigated for the possibility of colon cancer classification, though it did not include various classification issues with CLM.
- Diagnosis with usual traditional techniques like CT, MRI and so on is complicated to classify colon cancer as it requires high resolution.

III. COMPARATIVE ASSESSMENT METHODOLOGY UTILIZING DIVERSE DEEP LEARNING APPROACHES FOR COLON CANCER CLASSIFICATION

Colon cancer causes half a million death of people in every year as it frequently occurs. Researchers are working in present days for getting rid of physical investigation and to develop methods to detect colon cancer. Here, diverse deep learning techniques are compared to prove the effectiveness for colon cancer classification. In this assessment, an input image is considered from dataset and fed to pre-processing stage. Median filter is utilized for pre-processing to eliminate noises from input image. Afterwards, filtered image is passed to segmentation phase, where affected regions are segmented utilizing SegNet. Thereafter, segmented output is given to classification stagein whichclassification of colon cancer is performed utilizing deep learning methods like CNN, RNN, transfer learning, AlexNetand GoogLeNet. The diagrammatical presentation of comparative assessment methodology for classification of colon cancer is delineated in figure 1.

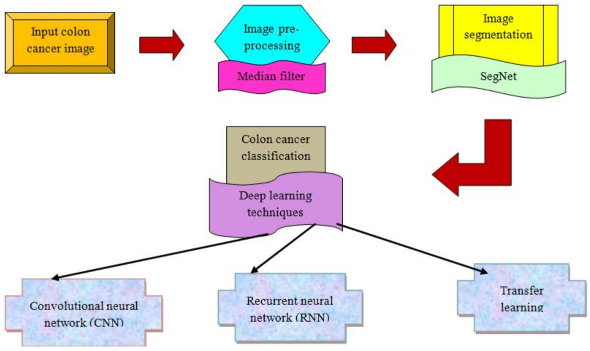

Figure 1. Diagrammatical presentation of comparative assessment methodology for classification of colon cancer

B. Acquisition of an image

Considering input colon cancer images in database C for classification of colon cancer obtained from certain dataset [26]. It can be represented by,

$$C = \{A_1, A_2, ..A_g, ..., A_t\} \tag{1}$$

Here, g^{th} input image is specified by A_g and total image samples in database are implied by A_t.

C. Image pre-processing utilizing median filter

An image pre-processing is a valuable stage, which is most significant for discarding noises from an image to process following phases. In this work, median filter is utilized, which is considered as non-linear filtering method generally employed for rejection of noises. This filter is vastly specified as order-statistical filter, which replaces pixel value utilizing gray values median in adjacent pixels. Median filter [20] is utilized extensively as it offers best noise elimination abilities. An output achieved through image pre-processing method is illustrated by,

$$F_g = \underset{(d,e)\in Qvw}{median} \{n(d,e)\} \tag{2}$$

D. Image segmentation utilizing SegNet

The pre-processed image F_g is then fed to segmentation stage wherein segmentation process is achieved effortlessly by means of SegNet. The major contribution of SegNet is mapping low-level contrast features for categorization in pixel-wise. This kind of depiction delivers the features, which are high desirable to boundary location. SegNet[21] is consisted of three kinds of layers namely encoder, decoder and softmax or pixel wise classification layer. For attaining higher contrast feature maps, the fully connected layer is eliminated. It also minimizes the count of parameters at an encoder network. The decoder outcome is passed to softmax for providing class possibilities.

(a) Encoder network: An encoder network consists of thirteen convolutional layers and operates convolutional functions with strainer bank for providing set of feature maps. These feature maps are thereafter batch-stabilized and element-wise function is applied utilizing Rectified Linear Unit (ReLU). Then, max pooling is performed and after that outcome is sub-sampled having parameter of about 2. The max-pooling is utilized for attaining translation unchanging, where sub-sampling is used for resulting larger spatial window.

(b) Decoder network: The decoder network has thirteen convolutional layers as like encoder network. The major operation of decoder is up-sampling of forthcoming feature maps utilizing max-pooling indices that results in a sparse feature maps and it executes convolution operation with trained decoder strainer bank for resulting concentrated feature maps. The next phase is operation of batch normalization procedure on each of the feature maps.

(c) Soft-max classifier: The larger dimension feature attained at decoder is subjected to softmax, which classifies each pixel individually. The softmax result is segmented image indicated by N_g.

E. Colon cancer classification using deep learning techniques

Colon cancer pathological performance fails to predict the repetition accurately and no gene expressive sign is proven trustworthy for prediction in medical practices, maybe because colon cancer is the heterogeneous disease. Here, several deep learning techniques like CNN, RNN, transfer learning, AlexNetand GoogLeNet are utilized for colon cancer classification to prove efficient classifier. An input considered for performing classification of colon cancer is implied by N_g.

1) CNN

CNN [22] is utilized for classification chores whereas an image is directly passed to CNN that learns for extracting related features and performs classification in output. The features that are computed inside convolutional layers are reutilized in following layers. In this manner, architecture of CNN is highly effective regarding to count of learnable parameters as the features are reutilized heavily. In the standard convolution, an overall feature is implicitly learned by means of summation. It comprises of series of layers for transforming input layer to an output layer. Various generally utilized layers are activation layer, convolutional layer, fully connected layer and pooling layer [27].

(a) Convolutional layer: In this layer, the neurons share similar biases and weights that are frequently known as filter or kernel. Correspondingly, an output for $(x, y)^{th}$ neuron is given by,

$$O_{x,y} = \sum_{\alpha=0}^{\eta-1} \sum_{\mu=0}^{\eta-1} W_{\alpha,\mu} u_{x+1,y+\mu} + B \quad (3)$$

(b) Pooling layer: The purpose of pooling layer is to partition neurons of prior layer into group of non-overlapping rectangles and executes down-sampling function on each of the sub-region for obtaining a value of single neuron in present layer.

(c) Activation layer: This layer applies element-wise nonlinearity and is generally utilized instantly after fully connected or convolutional layers.

(d) Fully connected layers: Each of the neuron in this layer is associated to each neuron of prior layer. An output of x^{th} neuron in fully connected layer is represented by,

$$O_x = \sum_y W_{xy} u_y + B_x \quad (4)$$

Here, W_{xy} represents a weight among y^{th} neuron of prior layer and x^{th} neuron of present layer whereas B_x indicates bias of x^{th} neuron of present layer. The output predicted by CNN is V_g.

2) RNN

RNN [23] is a category of artificial neural network, which extends conventional feed-forward neural network with the loops in links. Unlike, feed-forward neural network, RNN is capable for processing series inputs with recurrent hidden criteria wherein activation at each of the step depends upon prior phase.

For a given series of data $a = (a_1, a_2, \ldots, a_Z)$, where a_τ represents a data at τ^{th} time phase, then RNN updates the recurrent hidden state r_z as given below.

$$r_z = \begin{cases} 0, & if\ z = 0 \\ \phi(r_{z-1}, a_z), & otherwise \end{cases} \quad (5)$$

Here, ϕ denotes non-linear function. Optionally, RNN can have the output $k = (k_1, k_2, \ldots, k_Z)$. For few chores like classification of hyperspectral image, single output is needed that is given by k_Z.

In classical RNN techniques, an updated rule of recurrent hidden criteria in Eq. (5) is generally executed as follows.

$$r_z = \phi(R_{a_z} + S r_{z-1}) \quad (6)$$

Here, R and S represents coefficient matrices for an input at current phase and recurrent hidden unit activation at prior phase respectively. An output for colon cancer classification by RNN is signified by K_g.

3) Transfer learning

CNN generally performs in large datasets than small datasets whereas transfer learningis helpful in the applications of CNN, where datasets is not larger. The trained model from larger datasets like ImageNet is utilized for the applications with comparably small datasets.

Presently, transfer learning is utilized in several application fields like medical, screening of baggage and manufacturing. It eliminates the necessity of having larger datasets and also decreases longer training time, which is needed by deep learning techniques generated from scratch [28].

Transferable knowledge in the formation of expression features are extracted from a source area by feature learning techniques [29]. The source area data is indicated by,

$$T_Y = \left\{ (i_{Y1}; j_{Y1}), \left(i_{Ym}; j_{Ym} \right) \right\} \quad (7)$$

Here, $i_{Yb} \in I_Y$ denotes a data instance whereas consequent class label is given by $j_{Yb} \in J_Y$. Similarly, a target area data is represented by,

$$T_X = \left\{ (i_{X1}; j_{X1}), \left(i_{Xm}; j_{Xm} \right) \right\} \quad (8)$$

Here, input $i_{Xb} \in I_X$ whereas related output is $j_{Xb} \in J_X$; in most of the cases $0 < m_X << m_Y$. For a given learning chore X_Y from a source area T_Y and the learning chore X_X at target area T_X, transfer learning intends for developing a learning of objective predictive function $p_X(.)$ in T_X utilizing knowledge in T_Y and X_Y, where $T_Y \neq T_X$ or $X_Y \neq X_X$. The predicted output from transfer learning is denoted by D_g.

IV. RESULTS AND DISCUSSION

The results obtained by comparative assessment of various deep learning approaches are elucidated in this segment.

F. Experimental setup

The execution of this work is carried out for colon cancer classification in python tool on PC with intel core-i3 processor, 4 GB RAM and 10 OS.

G. Dataset description

The CT colonography dataset [26] comprises of 825 cases with XLS sheets, which provides polyp description and location inside colon segments. The number of series in this dataset is 3451 and number of images is 941,771 whereas image size is 462.6 GB.

H. Performance measures

An assessment of several deep learning techniques for colon cancer classification is investigated for the performance considering performance measures like specificity, accuracy and sensitivity.

1) Accuracy

Accuracy is referred to a metric utilized for classification problems to specify the percentages of accurate prediction. It can be illustrated by,

$$\mathrm{A} = \frac{\mathrm{T_N} + \mathrm{T_P}}{\mathrm{T_P} + \Im_\mathrm{P} + \mathrm{T_N} + \Im_\mathrm{N}} \quad (09)$$

Here, $\mathrm{T_N}$ and $\mathrm{T_P}$ are true negative and true positive results whereas $\Im_\mathrm{P}$ and $\Im_\mathrm{N}$ are false positive and false negative results.

2) Specificity

Specificity is defined as the metric that estimates the true negative predictions in each of the category. It is formulated by

$$\mathrm{Y} = \frac{\mathrm{T_N}}{\mathrm{T_N} + \Im_\mathrm{P}} \quad (10)$$

3) Sensitivity

It is a metric, which assess the true positive predictions in each of the category and given by,

$$E = \frac{T_P}{T_P + \Im_N} \quad (11)$$

I. Analysis with confusion matrix

The confusion matrix for classification of colon cancer with positive and negative cases is elucidated in figure 2. From the figure, it can be observed that from 45% of true cases of positive column, 20% is predicted as positive with colon cancer and 25% is predicted as negative with colon cancer. Similarly, from 35% of true cases of negative column, 15% is predicted as negative with colon cancer and 20% is predicted as positive with colon cancer.

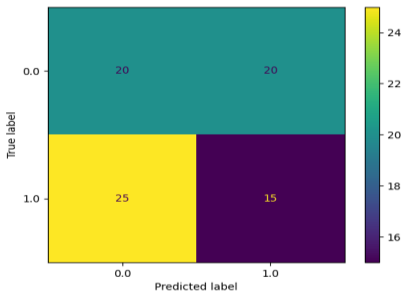

Figure 2. Confusion matrix for classification of colon cancer with positive and negative cases

J. Comparative techniques

The comparison assessment is carried out among several deep learning techniques like CNN [22], RNN [23], transfer learning [17], AlexNet [24] and GoogLeNet [25] with regard to metrics for evaluation.

K. Comparative analysis

The assessment is conducted for various deep learning approaches by varying percentages of training data and values of k-fold in terms of performance metrics.

1) Analysis based upon training data

Figure 3demonstrates a comparative assessment of various deep learning techniquesregarding to evaluation metrics by varying percentages of training data from60% to 100%. An evaluation of deep learning techniques on basis of accuracy is shown in figure 3 Accuracy attained by techniques likeCNN, RNN, transfer learning, 71.599, 76.599, 88.679whenpercentage of data=60%.Figure 3 delineates an analysis of several deep learning methods with respect to sensitivity. For 60% of data, sensitivity acquired by CNN is 71.685, RNN is 74.165, and transfer learning is 82.365. An estimation of specificity is illustrated in figure 3 Specificity attained by deep learning approaches like CNN, RNN, transfer learning are 69.265, 74.322, 78.652, while data is considered as 60%. Moreover, Transfer is proven as anbest classifier among the techniques for colon cancer classification in terms of performance measures.

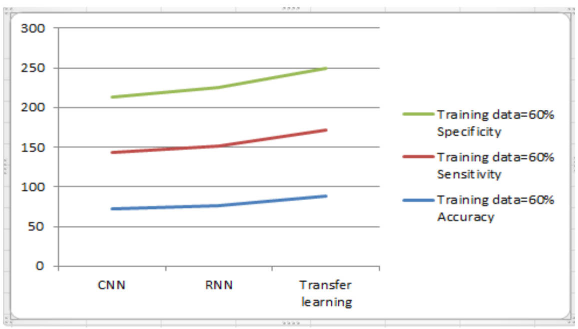

Figure 3. Assessment based on training data, a) Accuracy, b) Sensitivity, c) Specificity

2) ***Analysis based upon k-fold value***

An assessment of various deep learning techniques for colon cancer classification with regard to evaluation measures by varying k-fold values from 5 to 9 is represented in figure 4. Figure 4 interprets an evaluation of various deep learning methods with regard to accuracy. For k-fold value=5, accuracy achieved by CNN is

76.786, RNN is 79.674, transfer learning is 83.685. An estimation of deep learning techniques in terms of sensitivity is elucidated in figure 4 . Sensitivity achieved by methods like CNN, RNN, transfer learning are 73.499, 77.599, 84.547when k-fold value=5. Figure 4 also explains an estimation of deep learning methods with respect to specificityWhile k-fold value is considered as 5, specificity attained by CNN is 66.157, RNN is 71.499, transfer learning is 79.896. Therefore, transfer is confirmed as an effectual classifier while k-fold value is 5 based on performance measures.

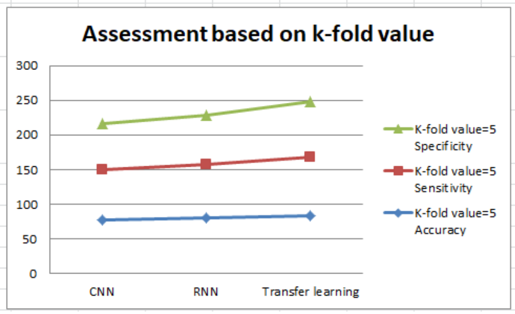

Figure 4. Assessment based on k-fold value, a) Accuracy, b) Sensitivity, c) Specificity

L. Comparative discussion

The comparative assessment discussion for several deep learning techniques to classify colon cancer is explicated in table 1. The below table recognizes Transfer learning is the best classifier for colon cancer classification.

TABLE 1. COMPARATIVE DISCUSSION

Analysis based on	Metrics/Methods	CNN	RNN	Transfer learning
Training data=60%	*Accuracy*	71.599	76.599	88.679
	Sensitivity	71.685	74.165	82.365
	Specificity	69.265	74.322	78.652
K-fold value=5	*Accuracy*	76.786	79.674	83.685
	Sensitivity	73.499	77.599	84.547
	Specificity	66.157	71.499	79.896

II. CONCLUSION

Colon cancer is referred as serious type of cancer having higher incidences as well as mortality rate in the developed regions. It occurs in both male and female, where these types of cancers are grouped together as they have several ordinary features. There are several deep learning techniques, which are utilized for colon cancer classification.Hence, this research focuses on comparative assessment of various deep learning techniques to find out the best classifier. The methodology phases involved for colon cancer classification are pre-processing, segmentation and finally, colon cancer classification. Initially, an input colon cancer is considered and given to pre-processing stage. The pre-processing is carried out utilizing median filter to remove noises in an input image. In segmentation phase, infected areas in filtered image are segmented using SegNet. Thereafter, colon cancer classification is done employing deep learning approaches like CNN, RNN, transfer learning. These techniques are compared to identify effective classifier for colon cancer classification. In order to achieve the more accuracy for detecting the colon cancer google net and alex next are combined with any Hybrid Optimization algorithm.

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