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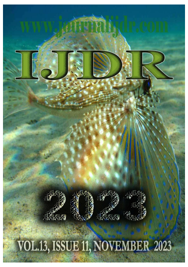

RESEARCH ARTICLE

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CLASSIFICATION OF COLON CANCER BY USING CNN AND CAPSULE NEURAL NETWORK

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ABSTRACT

Colorectal cancer typically originates as a button-like growth termed a polyp on the surface of the intestinal lining or rectum. The intestine or rectumdivision may invade nearby or adjacent lymph nodes. Due to the fact that blood flows from the intestine's wall and asubstantial portion of the rectum to the liver, colorectal cancer can metastasize to the liver after spreading to adjacent lymph nodes. Machine Learning obtained a good performance for colon cancer detection. However, the cancer detection systems based on ML need manual detection of the features and separate classifiers for the detection, making the system more complex and time-consuming when using big data. There are several traditional techniques which are not flexible, robust and time consuming as they are devised for manual assessment of colon cancer. Hence, in this research several deep learning techniques namely convolutional neural network (CNN) and Capsule Neural Network are compared. The comparative assessment showed Capsule Neural Performs Better than CNN.

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INTRODUCTION

Colon cancer is the second most common cause of cancer death in women and the third most common cause of cancer death in men. If cancer is not diagnosed in its early stages, there is a great likelihood that it will spread to the two organs. Early detection of colon cancer can significantly facilitate clinicians' decision-making and reduce their workload. Thiscan be achieved using automatic systems with endoscopic and histological images. Earlier studies relied on DL modelsrequired great computational ability and resources and showed more misclassifications. This paper proposes a noveltechnique for colon cancer detection which will be implemented as followsCancer signifies to a categorization of illness wherein abnormal cells are developed inside human body as an outcome of random alterations (Tasnim, 2021). 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 (Labianca, 2010). 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 (Lannagan, 2021). 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 (Zauber, 2012). The number of guidance is established forendoscopic observation of high danger groups to identify colon cancer (Freeman, 2013). When healthier cells and lining of colon or rectum expands in an uncontrollable manner, a cancer occurs. This kind of cancer is generally malignant (Lannagan, 2021 and Ali, 2021). Adenocarcinoma of colon or rectum generally develops with large intestine lining, beginning in epithelial cells and spreads to other layers (Ali, 2021). 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 (Freeman, 2013). Additionally, upstaging of the colon cancer results from utilization of magnetic resonance imaging (MRI), position emission tomography, computed tomography (CT) (Khan, 2020), ultrasound with pathological confirmations (Freeman, 2013). In recent times, digital pathology is emerging as vital tool for prognosis and diagnosis of cancers (Gurcan, 2009 and Hamidaa, 2021). 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 (Pantanowitz, 2010). These images plays a main part in a process of pathological diagnosis (Snead, 2016; Pantanowitz, 2013; Amin, 2019) because it enables easier data storing and sharing (Hamidaa, 2021). Presently, a novel intra-operative device utilizing confocal laser microscopy (CLM) is presented, which offers submicrometer image resolutions (Ellebrecht, 2019). Nowadays, automated tissue classification has been addressed successfully utilizing deep learning techniques (Fernandis, 2021) like CNN for the semantic segmentation as well as classification (Litjens, 2017; Gessert, 2019). 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 (Afshar, 2020; Koresh, 2020 and Ali, 2021). 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 and Capsule Neural Network. 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.

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.

LITERATURE SURVEY

The survey done utilizing the existing deep learning methods are interpreted as follows. Nils Gessert *et al*. (Gessert, 2019) 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. Lichao Mou *et al*., (Mou, 2017) 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*. (Gessert, 2019) 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*. (Sustika, 2018). Evaluated GoogLeNet for improving the performance, which showed rapid speed but it needs many resources for computation.

Major Challenges

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

- CNN utilized in (Gessert, 2019) 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 (Gessert, 2019), 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.

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. [30]NLM 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 and Capsule Neural Network.The diagrammatical presentation of comparative assessment methodology for classification of colon cancer is delineated in Figure 1.

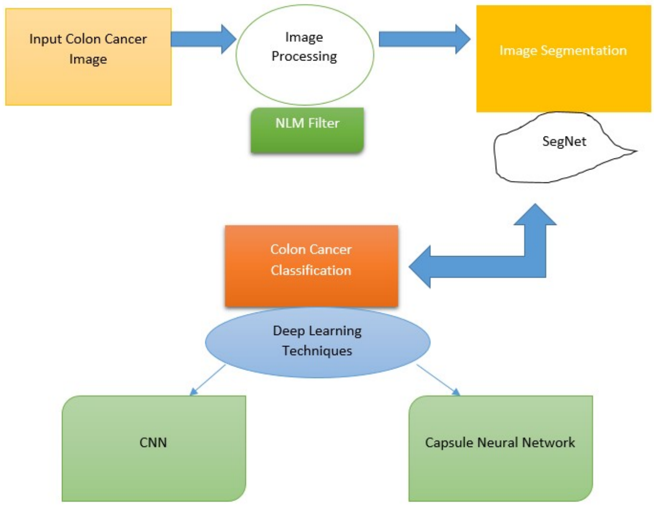

Figure 1. Diagrammatical presentation of comparative assessment methodology for classification of colon cancer

Acquisition of an image: Considering input colon cancer images in database C for classification of colon cancer obtained from certain dataset (Colonography dataset taken from, 2022). It can be represented by,

$$C = \{A_1, A_2, \ldots A_g, \ldots, A_t\} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

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

Image pre-processing utilizing nlm 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,

$$F_{NLM}(l) = \sum u(l, j)x(j) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

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.

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 and Capsule Neural Network.

CNN: CNN (Gessert, 2019) 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 (Huang, 2019).

(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,

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

(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,

$$O_x = \sum_y W_{xy} u_y + B_x \qquad \text{..................(4)}$$

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.

Capsule Neural Network: The key components of the CapsNet are the encoder and decoder, where the encoder has three layers and decoder has the three layers. The vector capsules are the lowest level capsules that take the small portions of the image as input. Here, the routing capsules are the higher level capsules that helps in detecting bigger and complicated problems. The outcome of the capsules are will be in the form of a vector and the length of every vector signifies the expected probability for the existence of the object.

RESULTS AND DISCUSSION

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

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.

Dataset description: The CT colonography dataset (Colonography, 2022) 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.

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.

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

$$A = \frac{T_N + T_P}{T_P + \Im_P + T_N + \Im_N} \qquad \text{........................(5)}$$

Here, T_N and T_P are true negative and true positive results whereas $\Im_P$ and $\Im_N$ are false positive and false negative results.

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

$$Y = \frac{T_N}{T_N + \Im_P} \qquad \text{..........................(6)}$$

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

$$E = \frac{T_P}{T_P + \Im_N} \qquad \text{.........................(7)}$$

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.

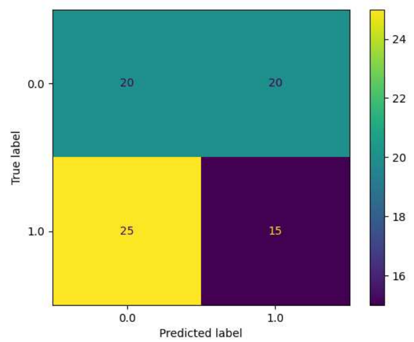

Figure 2. Confusion matrix for classification of colon cancer with positive and negative cases

Summary of Capsule Neural Network

Layer	Input Layer	input	Output
conv2d_1_input	InputLayer	(None,256,256,3)	(None,256,256,3)
conv2d_1	Conv2D	(None,256,256,3)	(None,62,62,96)
activation_1	Activation	(None,62,62,96)	(None,62,62,96)
batch_normalization_1	BatchNormalization	(None,32,32,96)	(None32, 32, 256)
Primary Cap(conv2d_2)	Conv2D	(None,32, 32, 256)	(None,32, 32, 256)
activation_2	Activation	(None,52, 52, 256)	(None,52, 52, 256)
max_pooling2d_1	MaxPooling2D	(None,52, 52, 256)	(None,26,26,256)
batch_normalization_2	Batch Normalization	(None,26,26,256)	(None,26,26,256)
Capsule Layer (conv2d_3)	Conv2D	(None,26,26,256)	(None, 24, 24, 384)
dense_1	Dense	(None, 16384)	(None,4096)
dense_2	Dense	(None,4096)	(None,4096)
dense_3	Dense	(None,4096)	(None,4096)
Reshape	Reshape	(None,4096)	(None,4096)

Table 1. Comparative discussion

Analysis based on	Metrics/Methods	CNN	Capsule Neural Network
Training data=60%	*Accuracy*	71.599	91.888
	Sensitivity	71.685	90.300
	Specificity	69.265	92.530
K-fold value=5	*Accuracy*	76.786	91.485
	Sensitivity	73.499	90.758
	Specificity	66.157	92.777

Comparative techniques: The comparison assessment is carried out among several deep learning techniques like CNN (Gessert, 2019), Capsule neural Network.

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.

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 NLM 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 several deep learning approaches like CNN and Capsule Neural network are utilized. Capsule neural Network outperformed the CNN in Accuracy, Sensitivity and Specificity values. As a future task, the best classifier will be assessed considering other performance measures and compares with existing techniques to prove its efficacy for colon cancer classification.

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