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Deep Learning-Based CNN Model for Early Detection and Classification of Colorectal Cancer

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Abstract: The timely identification of colorectal cancer can greatly aid in the decision-making process and alleviate the burden on medical professionals. Histological and endoscopic image-based automation systems can be used to accomplish this. Recently, the success of deep learning has motivated the development of image- and video-based polyp identification and segmentation. Artificial intelligence techniques are being used in the majority of diagnostic colonoscopy rooms, and they are thought to be effective in predicting invasive malignancy. Preprocesses, picture patches, and designs based on convolutional neural networks are frequently utilized. Moreover, end-to-end learning and learning transfer methods have been used for detection and localization tasks, which decrease user reliance and increase accuracy with small datasets. Explainable deep networks, on the other hand, are favored because they offer clinical diagnoses with transparency, interpretability, reliability, and equity. In this review, we summarize the latest advances in such models, with or without transparency, for the prediction of colorectal cancer and also address the knowledge gap in the upcoming technology. The public availability of digital pathology datasets has made it possible to assess if using deep learning techniques to enhance the effectiveness and caliber of histologic diagnosis is feasible. This article proposes a model that uses the Convolutional Neural Network and Ranking algorithm to identify colorectal cancer. Based on the performance evaluation, it is found that the proposed model is yielding better results in diagnosis of Colorectal Cancer than the existing methods in terms of Recall, Precision and Accuracy.

Keywords: Detection, Colorectal Cancer, Deep Learning, CNN, Decision Making

1. INTRODUCTION

The most effective method of preventing colorectal cancer is thought to be endoscopic excision of precancerous lesions. The prognosis of patients with colorectal cancer can be improved by early detection of cancerous lesions; thus, there is a need for reliable, early, and accurate endoscopic diagnosis The most reliable method for detecting colorectal lesions is a colonoscopy [7,8,9]. But depending on the expert's endoscopic competence, the rate of missed polyp detection during colonoscopy rises [10,11,12]. Hence, artificial intelligence (AI) technologies could help in reducing the skill gaps among clinicians and thereby decrease the rate of missed lesions during colonoscopy

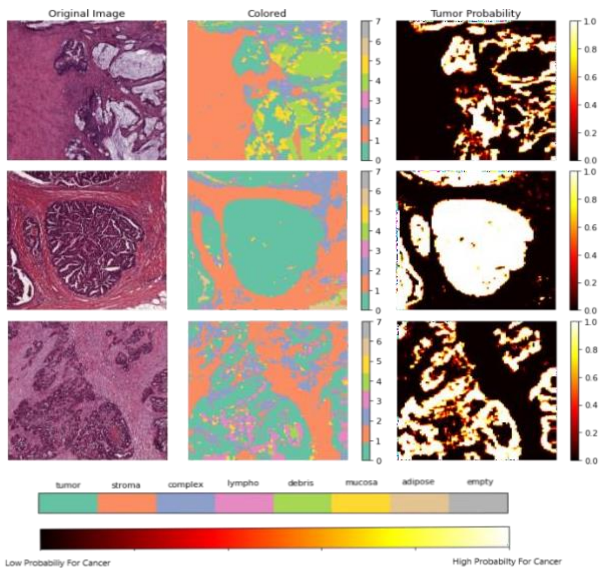

Figure 1 . Colorectal Cancer Images

2. LITERATURE SURVEY

Colon and rectal cancer are frequently suggested jointly because of their similar characteristics. Deep learning was used in this study to examine colorectal, rectal, and other malignancies connected to colon cancer [17, 18, 19, 20, 30]. Standard deep structures based on convolutional neural networks (CNNs) have been widely utilized to segment and categorize colon lesions as being different from other undesirable regions.

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Currently, the majority of artificial intelligence (AI) used in computer-aided diagnostic systems, as mentioned in the literature, heavily depends on elaborate manual parameter configuration for extracting feature patterns. This approach has a direct impact on the results obtained.

Prior to installing a neural network, it is necessary to employ hand-crafted features together with a feature selection module.

This enables the automatic interpretation of the features and significantly enhances the accuracy of colorectal cancer diagnosis. Two distinct colorectal cancer neural networks optimized for segmenting and classifying colon glands successfully detected both benign and malignant cancer with high accuracy [33]. While these systems demonstrated amazing performance, their frameworks often exhibited inadequate performance in detecting fluctuations in lumen and gland volumes. This may be due to manual parameter settings for reducing various illumination conditions, which affects the region of interest for the classification of features. Such bias is unfavorable for the detection of lesions.

Main Steps:

First Dataset:

1. Partitioning the images in the initial dataset into 90% training and 10% testing portions.
2. Employing a VGG16 model with a bespoke classifier as the top layer to accurately analyze photos from the initial dataset.
3. Utilise data augmentation, unfreezing, and fine tuning techniques to enhance research outcomes.

Second Dataset:

4. Cutting the big pictures (5,000x5,000) into 150x150 parts to fit the model's input
5. predicting the class of each cropped window and combining the windows back to 5000x5000 image for each image from second dataset

2.1 DATA PREPROCESSING

Firstly, we augment the data to simply increase the quantity of data. Data Augmentation [18] is a process that generates several realistic variants of each training sample, to artificially expand the size of the training dataset. This facilitates the mitigation of overfitting. In data augmentation, we will slightly shift, rotate, and resize each image in the training set by different percentages, and then add all the resulting photos to the training set. This allows the model to be more forgiving of changes in the object's orientation, position, and size in the image. The result of each of these data sharing will be compared to the results of its accuracy to determine which is better in dividing in the proportion of data.

3. PROPOSED METHODOLOGY

The proposed ranking based colorectal cancer detection model has the following steps:

1. Image Pre-processing
2. Image Segmentation
3. Feature Extraction using CNN
4. Classification based on Ranking Algorithm

CNN is a supervised learning method where the identification of the image is by training the existing dataset and targeting image variables. The convolutional layer in CNN helps the neural network recognize colon cancer based on their attributes. The neural network utilizes pixels extracted from the image to accurately identify colon cancerlef images. In this project, we will be using an image with size of 256 X 256 X 3, where it will have three channels, which are red, green, and blue (RGB).

We will apply MaxPooling to the final image. In the next step, this layers us being flattened. The Relu, which is a nonlinear activation function, is used in the hidden layers, while the output layer has the SoftMax activation function. This project has the proposed model for CNN architecture in identifying diseases in colon cancer using 6 convolutional layers and 6 MaxPooling layers as shown in figure 3.

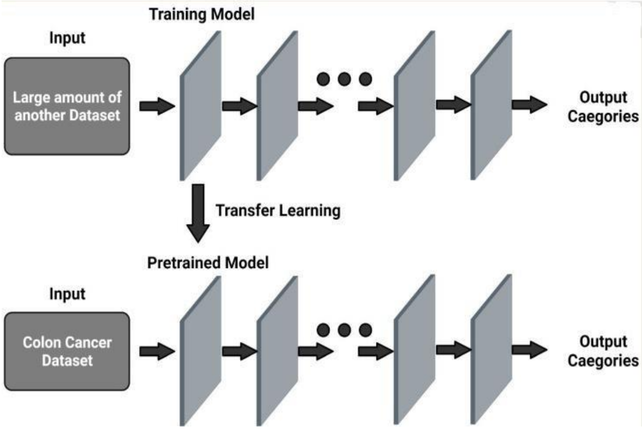

Figure 2. Transfer Learning Model for Colon Cancer

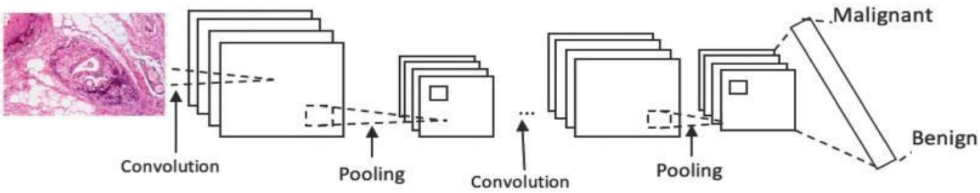

Figure 3. CNN Model for Colorectal Cancer

3.3.1. Input layer

The input layer is the network's starting point. Aside from normalizing, segmenting, and removing foreground and background objects, preprocessing techniques like converting to grayscale and increasing efficiency are used to lower the computing cost of the approach.

3.3.2. Convolution layer

The convolution layer performs two-dimensional convolution on a three-dimensional input layer and a three-dimensional filter layer. In case, the size of the input is H × W × C, where height is H, width is W, and the channels is C. Therefore, the dimensions of the filter are HF × WF × C, with HF and WF denoting the height and width of the filters, respectively. An equal channel size is allocated to both the input and filter. 2D convolution is performed in the vertical and horizontal dimensions.

3.3.3 Layer of non-linearity

A non-linear function is used by the activation function of the convolution layer to assist normalize the input image pixels. The Rectified Linear Unit (ReLU) yields the same value for all inputs except negative inputs, which causes it to return zero.

3.3.4. Pooling layer

The pooling layer minimizes the training time and addresses the over-fitting issue by reducing the network dimensionality. The widely used minimization techniques are: determining the mathematical mean Choosing the pixel with maximum value Choosing the sum of all the elements

When the pooling function is used, the outputs of the ReLU layers are replaced by a summary of the outputs of the adjoining layers. This has two distinct benefits:

1. the representation is invariant to small variations in the input
2. lessens the amount of work of the computer.

3.3.5. Fully connected (FC) layer

Both the total convolution layer and the pooling layer are components of the FC layer. This layer is responsible for performing high-level analysis in order to extract the feature representations from the outputs of the layers that came before it. In a multiclass classification, the number of outputs is equal to the number of classes that are specified in the fully linked layer of the classification. When it comes to the classification problem, the softmax function is the one that is strongly recommended.

A representation of the proposed ranking algorithm can be described using the phases that are as follows: Rank the features based on TP Score (TPS) – FP Score (FPS) Eliminate the features with minimum FPS Combine the selected features based on the Feature selection algorithm

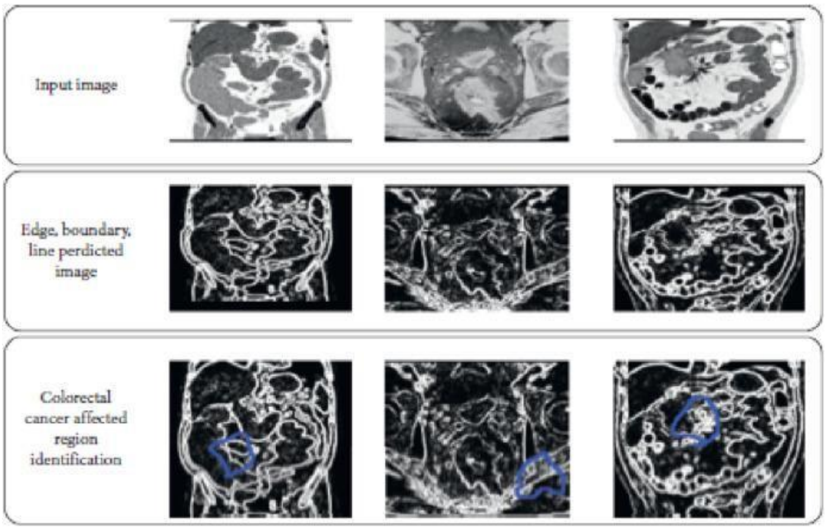

Figure 4 Summarizes the entire quantity of both trainable and non-trainable parameters**.**

One of the fundamental components that makes up CNN is the convolution layer. The majority of the computational burden that the network is responsible for is carried by it. A two-dimensional representation of the image, also known as an activation map, is produced as a result of this process. This activation map provides the response of the kernel at each spatial position of the overall image. If we have an input that is W x W x D and an output number of kernels that are D in size, with a spatial dimension of F, stride S, and amount of padding P, then the following formula can be used to compute the size of the output volume:

$$W_{out} = \frac{(W - F + 2P)}{S + 1}$$

It is possible to map the representation between the input and the output with the assistance of the completely linked layer. Utilizing the equation, it was carried out as follows:

$$Z\text{L} = W\text{L} * h_{l-1}$$

CNN is utilized in order to construct the sequential model. In order to accomplish this, we have utilized rectified linear units. SoftMax is also used as an activation for forecasting, which depends on the maximum likelihood. The equation for the SoftMax function is given below:

$$softmax(Z) = \frac{e^{X^T}}{\Sigma^k\ e^{X^T}}$$

Here, the internal product of X and T is indicated by the SoftMax of z. The input width (nm) and height (nh) of the first convolutional layer are 256 and 256 respectively. The dimension of the max-pooling layer output was calculated using the Equation:

$$Dimension(Conv(n, k)) = ([\frac{n_\text{m} - f_\text{m}}{s} + 1\ ]\ , [\frac{n_\text{h} - f_\text{h}}{s} + 1]\ , fc\ )$$

ReLu is more dependable and accelerates convergence by six times compared to sigmoid and tanh. The ReLu activation function was performed by using the equation:

$$ReLu(x) = Max(0, x)$$

4. RESULTS AND DISCUSSIONS

Training Simple CNN...
Epoch 1/10
1/1 [==============================] - 21s 21s/step - loss: 0.7222 - accuracy: 0.0000e+00 -
preciEpoch 2/10
1/1 [==============================] - 18s 18s/step - loss: 0.0235 - accuracy: 1.0000 -
precisionEpoch 3/10
1/1 [==============================] - 19s 19s/step - loss: 6.2565e-05 - accuracy: 1.0000 -
preciEpoch 4/10
1/1 [==============================] - 18s 18s/step - loss: 4.7518e-08 - accuracy: 1.0000 - preci
Epoch 5/10
1/1 [==============================] - 19s 19s/step - loss: 1.5750e-11 - accuracy: 1.0000 -
preciEpoch 6/10
1/1 [==============================] - 20s 20s/step - loss: 2.9726e-15 - accuracy: 1.0000 -
preciEpoch 7/10
1/1 [==============================] - 16s 16s/step - loss: 4.0245e-19 - accuracy: 1.0000 -
preciEpoch 8/10
1/1 [==============================] - 16s 16s/step - loss: 4.6138e-23 - accuracy: 1.0000 -
preciEpoch 9/10
1/1 [==============================] - 18s 18s/step - loss: 5.0953e-27 - accuracy: 1.0000 -
preciEpoch 10/10
1/1 [==============================] - 18s 18s/step - loss: 6.0889e-31 - accuracy: 1.0000 -
preciTraining VGG16...
Epoch 1/10
1/1 [==============================] - 22s 22s/step - loss: 0.6035 - accuracy: 0.9000 -
precisionEpoch 2/10
1/1 [==============================] - 19s 19s/step - loss: 0.4099 - accuracy: 1.0000 -
precisionEpoch 3/10
1/1 [==============================] - 20s 20s/step - loss: 0.2729 - accuracy: 1.0000 -
precisionEpoch 4/10
1/1 [==============================] - 19s 19s/step - loss: 0.1803 - accuracy: 1.0000 -
precisionEpoch 5/10
1/1 [==============================] - 19s 19s/step - loss: 0.1197 - accuracy: 1.0000 -
precisionEpoch 6/10
1/1 [==============================] - 29s 29s/step - loss: 0.0804 - accuracy: 1.0000 -
precisionEpoch 7/10
1/1 [==============================] - 20s 20s/step - loss: 0.0553 - accuracy: 1.0000 -
precisionEpoch 8/10
1/1 [==============================] - 31s 31s/step - loss: 0.0387 - accuracy: 1.0000 - precision
Epoch 9/10
1/1 [==============================] - 21s 21s/step - loss: 0.0278 - accuracy: 1.0000 –
precisionEpoch 10/10
1/1 [==============================] - 19s 19s/step - loss: 0.0204 - accuracy: 1.0000 - precisionTraining
ResNet50...
Epoch 1/10
1/1 [==============================] - 24s 24s/step - loss: 0.5337 - accuracy: 1.0000 - precisionEpoch
2/10
1/1 [==============================] - 19s 19s/step - loss: 0.3575 - accuracy: 1.0000 - precisionEpoch
3/10
1/1 [==============================] - 18s 18s/step - loss: 0.2345 - accuracy: 1.0000 - precisionEpoch
4/10
1/1 [==============================] - 17s 17s/step - loss: 0.1539 - accuracy: 1.0000 - precisionEpoch
5/10

1/1 [==============================] - 17s 17s/step - loss: 0.1040 - accuracy: 1.0000 - precisionEpoch 6/10

1/1 [==============================] - 20s 20s/step - loss: 0.0717 - accuracy: 1.0000 - precisionEpoch 7/10

1/1 [==============================] - 21s 21s/step - loss: 0.0504 - accuracy: 1.0000 - precisionEpoch 8/10

Evaluating Simple CNN...

1/1 [==============================] - 9s 9s/step - loss: 8.6777e-35 - accuracy: 1.0000 - precisi

Evaluating VGG16...

1/1 [==============================] - 11s 11s/step - loss: 0.0153 - accuracy: 1.0000 - precision

Evaluating ResNet50...

1/1 [==============================] - 9s 9s/step - loss: 0.0158 - accuracy: 1.0000 - precision_4

Evaluating InceptionV3...

1/1 [==============================] - 9s 9s/step - loss: 8.0923e-10 - accuracy: 1.0000 - precisi

Evaluating EfficientNetB0...

1/1 [==============================] - 9s 9s/step - loss: 0.0014 - accuracy: 1.0000 - precision_4Model

		Loss	Accuracy	Precision	Recall
0	Simple CNN	8.677735e-35	1.0	0.0	0.0
1	VGG16	1.531761e-02	1.0	0.0	0.0
2	ResNet50	1.581965e-02	1.0	0.0	0.0
3	InceptionV3	8.092259e-10	1.0	0.0	0.0
4	EfficientNetB0	1.406688e-03	1.0	0.0	0.0

Figure displays the accuracy and loss curves of the training and validation datasets. An overall accuracy of approximately 98% was deemed satisfactory for our test dataset. displaying the Simple CNN predictions visually...

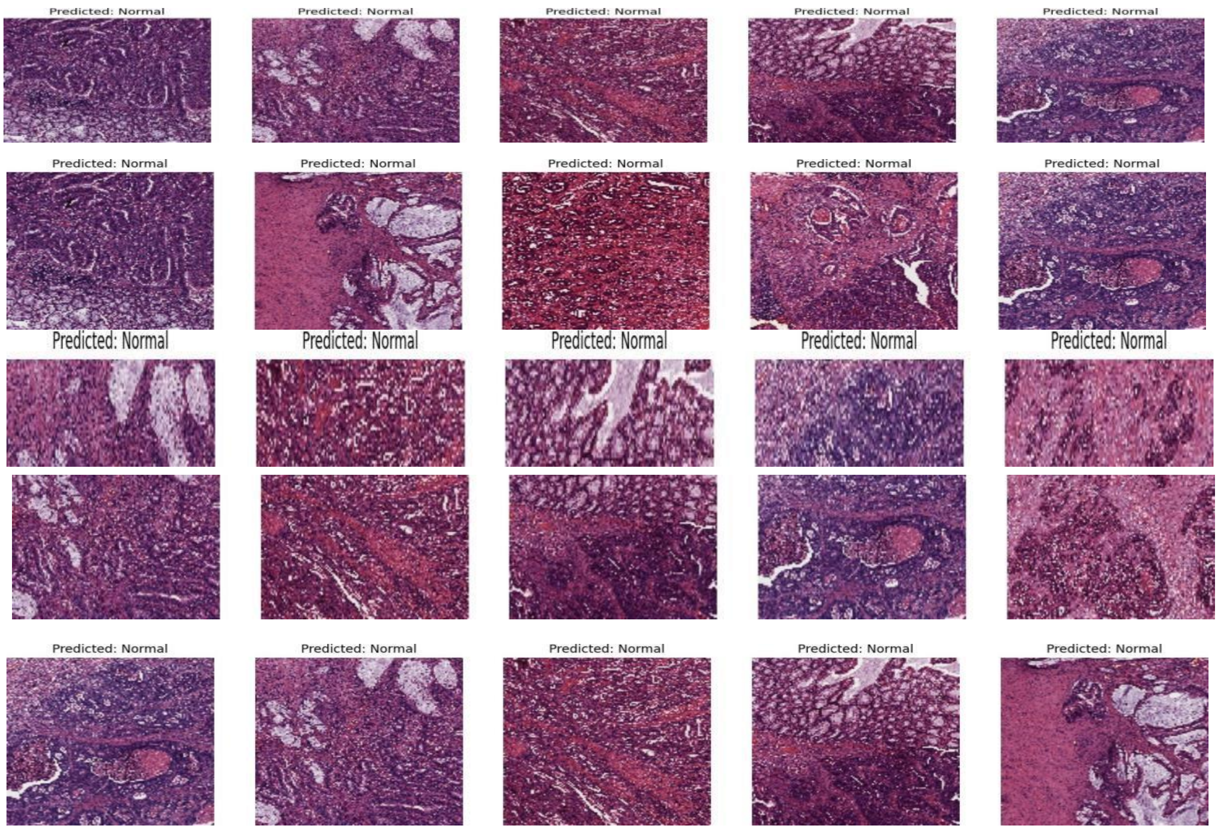

Figure 5. Implementation of Identification of Colorectal Cancer

The predictions produced by the categorization algorithms are summarized in the confusion matrix. The true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values for each class are represented in the classification technique's confusion matrix. The area under the receiver operating characteristic (AUC-ROC) curve is one of the popular metrics that are used to evaluate the performance of learning algorithms. The following equations are used to determine the TPR and FPR:

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

A table used to describe a classification model's performance is called a confusion matrix. It displays and provides an overview of a classification model's performance. In this case, we create a graph to illustrate the comparison of the true and forecasted numbers. Recall is the most crucial performance evaluation method. Recall is calculated by dividing the total number of results that were successfully identified by the total number of results that were wrongly rejected. The percentage of genuine positives that were successfully detected is ascertained using the recalls. One of the metrics

$$Classification\ accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = 2 *(precision * recall)\ (precision + recall)$$

CONCLUSION

Overall, the suggested investigation indicated that AI is showing promise in terms of colorectal cancer diagnosis accuracy. However, the user-dependent and sophisticated, non-transparent deep network models do not give an appropriate level of evidence for the important elements utilized in classification, which explains why this technique has been reluctant to be implemented in clinical practice. Most AI models used to forecast invasive cancer are prone to over-detection.

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