CNN-Based Colon Cancer Recognition Model

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***Abstract*— Digital pathology is being used extensively for the diagnosis of tumors. Disappointingly, the existing approaches are still constrained whenever confronted with a resolution, a size of images, and a lack of extensively cleaned datasets. Further, the recognition accuracy mostly does not reach high scores. In terms of Deep Learning (DL) approaches' capacity to handle extensive applications, such an approach appears to be an absorbing solution for both categorization and tissue segmentation in histopathology images. The present study concentrates on the application of deep learning models in the classification of the context of histopathology data and the recognition of colon cancer. In this, cutting-edge Fully Convolutional Network (CNN) models such as DenseNet121, EfficientNetB7, EfficientNetB1, EfficientNetB2, and DenseNet201 have been evaluated for the recognition of Colon Cancer. The assessment of the algorithms used for the proposed CNN-based colon cancer detection model ensures reliable classification findings with EfficientNetB2 attaining up to 99.9994% in terms of accuracy.**

Keywords—Colon Cancer, Deep Learning, DL, Cancer Recognition.

I. Introduction

Cancer has become one of the main serious illnesses affecting human health, with a significant fatality rate. Abnormal cells are caused by malignancies. There are benign tumors that are not malignancies and frequently treated. They are seldom hazardous since they hardly reoccur. On the contrary side, malignant tumors or malignancies are harmful because they develop aggressively. Several cell bodies begin to divide and spread into the surrounding organs aggressively. According to the National Cancer Institute (NIH), about 609,360 individuals will pass away and about 1,918,030 new cancer cases will be identified in the United States in 2023 [1]. Colon cancer is one of the most fatal cancers. It is known as colorectal cancer which is a dangerous disease that has a high fatality percentage in industrialized countries. It is the 3rd commonly diagnosed cancer for both women and men in many countries like the United States, and Turkey [1, 2]. In Turkey, the yearly rate of colon cancer (CRC) is roughly estimated as 7 individuals in every 100,000 people, with 3,200 death cases and approximately 5,000 new cases every year [2]. Due to some characteristics, rectal and colon cancers are sometimes lumped together.

The unique characteristics of histopathology pictures have sparked efforts to develop advanced machine vision algorithms to detect cancer. On such setting can minimize doctors' effort, synchronize practical significance, and cut both processing and handling time. Indeed, AI technologies have gradually progressed from intelligent machines to classical Machine Learning (ML) and Deep Learning (DL). In other words, in the traditional handcrafted methodologies, data analysis activities were heavily reliant on professional expertise to specify critical attributes. In contrast, contemporary DL networks have the capability to automatically recognize characteristics from data in a more accurate and user-friendly method [3].

Several computer-aided diagnostics (CAD) technologies have subsequently been built to automatically screen the indicators of malignancy or tumor progression in the human body such as skin [4], liver [5], and colon tissues [6-10]. The prevalent AI advances in colon cancer recognition success, which can be attributed to artificial intelligence (AI), are (1) the identification of colorectal cancerous tissues through the use of machine-learning techniques, with the classification and analysis of histopathology images [11, 12] and (2) the recognition of colorectal cancer by using advanced DL methods such as CNN with histopathology images [6-10].

Ozawa et al. [13] used a special architecture of CNN to build Single Shot MultiBox Detector (SSD) in order to present both polyp identification and polyp classification techniques. They employed a non-public dataset; and their research found that CNNs performed well in the detection of colon cancer. Moreover, Soberanis-Mukul et al. [14] provided a polyp localization system based on RetinaNet. This idea was motivated by learning to use the artifact information shown in the polyp photos. The influence of the application of polyp identification was done using this paradigm. It was the first study to employ artifacts in polyp identification at the same time. Additionally, Zeng et al. [15] presented a CNN-based architecture that employed optical tomographic images to differentiate between healthy and malignant colon cells.

Tongaçar [6] demonstrated the method to classify lungs and colorectal cancer using an AI-powered algorithm and optimizing approaches based on histopathology scans. DarkNet-19 model was applied for training the model from scratch using the image categories, and then a Support Vector Machine (SVM) was employed to categorize the characteristics. Consequently, the suggested method reached the correct detection rate of about 99.69%. A study by Yildirim and Cinar [8], diagnosing colon cancer, employed a 45-layer model known as MA ColonNET which achieved an accuracy of 99.75%. This model/method can identify colorectal cancerous tissues rapidly and simplify treatments.

Wang et al. [16], suggesting a new anchor-free approach for detecting polyps in a timely manner, made considerable gains in this domain by using a CenterNet-based design and a VGG16 network. The authors deleted the center pooling in the CenterNet topology to gain complete identification and obtained a quicker recognition. Furthermore, to avoid recollection loss, they presented a cosine ground-truth prediction approach and got a more efficient polyp detector.

Nadimi et al. [17] proposed an end-to-end CNN-based model that uses deep-learning techniques for colorectal polyp identification in images obtained during a wireless colonic capsule endoscope. To locate portions of colorectal polyp pictures, they employed the Rapid R-CNN method. In addition to the information proveided, 11,300 capsule endoscopic pictures were obtained for training and testing processes. This investigation outperformed other previously published studies and newer methodologies in terms of accuracy, precision, and specificity. It achieved an accuracy of 98.0%, a specificity of 96.3%, and a sensitivity of 98.1%.

This paper provides a CNN-based model that can detect colon cancer from digital images. The fundamental obstacles of its advancement are also discussed, with a specific emphasis on DL approaches for medical image classification. As a result, beside the dataset used here, several DL models have been developed and applied to colon cancer histopathology image identification. So, for effective colorectal cancer diagnosis, a robust end-to-end DL-based approach has been followed. Unlike the prior techniques, the suggested approach is more straightforward and has fewer layers. Furthermore, unlike most past efforts, the solution is complete without the need for any external traditional Machine learning steps such as extracting feature stage or features selection stage. Most prior deep learning algorithms in this domain were outperformed by the proposed model. The suggested system's efficiency is evaluated by using a histopathological image database versus the existing Cutting-edge approaches for image classification. Additionally, unlike other approaches, the suggested EfficentNet-based model attained a high accuracy.

To illustrate the structure of the paper, the following sections are: Section II discusses the data interpretation, specifics of preparation, and the methodology of the modeling techniques used; Section III discusses research findings; and finally Section IV which is the conclusions and the limitations of the study given in the form of critical summation.

II. Methodology

Herein, the proposed approach and fundamental techniques used to detect colon cancer from medical images have been illustrated. Figure (1) shows a conceptual depiction of the suggested approach. The main objective of this work is to diagnose colon cancer using histopathology images. The raw histopathology pictures are initially rescaled to fit the proposed CNN input layer, which reduces the processing time interval. This followed by standardizing the histopathology images before being forwarded to the CNN algorithms for detecting colorectal cancer. The validation split strategy to create the parts of the dataset of this model was carried out by dividing all dataset images into 70% as the train set, 20% as a validation set, and the remaining 10% used for testing. We examined five deep architectures with varied batches and fine-tuning parameters and afterward chose the best-performing design to be the model of the present study.

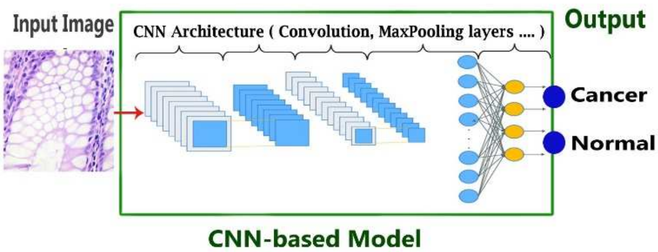

Fig. 1. The proposed Colon Cancer Detection Model.

A. Dataset Description

The dataset that has been used in this study is called “Lung and Colon Cancer Histopathological Images” downloaded from Kaggle website and related to the paper [18]. The images of colon tissues were taken into account. In the dataset, there are about 10000 images belonging to two classes. The first category includes histopathological images of normal tissues, and the second category contains images of cancerous tissues. Dataset details are illustrated in (Table I).

TABLE I. Dataset Details

Class	The Images in the dataset		
	Training	*Validation*	*Testing*
Normal	3500	1000	500
Cancer	3500	1000	500

A simple cancerous histopathological image of normal tissue and a histopathological image of cancerous tissue are indicated in the next illustration (Fig. 2).

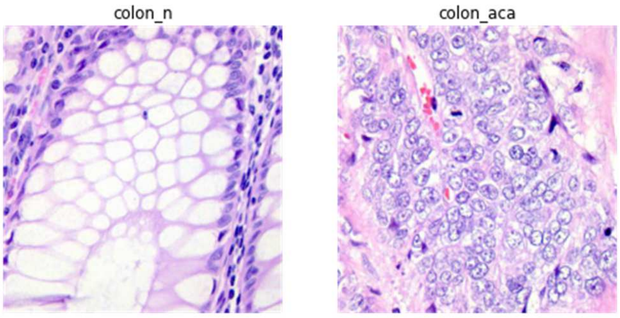

Fig. 2. The image of normal tissue is on the left and cancerous tissue image is on the right.

B. Training the Classifiers

Five classification techniques including three classifiers from the EfficientNet family (EfficientNetB7, EfficientNetB1, EfficientNetB2), DenseNet169, and DenseNet201 are utilized during this phase. Each model had been fine-tuned using different steps including freezing the upper 5 layers and removing the last four layers from the original model architecture. During training, the early stopping callback is used with a patience value of 2, BATCH_SIZE (128), lr=0.0001, momentum=0.9, and Adam optimizer. The last four layers are as follows: GlobalAveragePooling2D, Flatten layer, two Dense layers with Relu activation functions, and a DenseLayer with 2 output (number of classes) and SoftMax classifier as an activation function. The classifier's weights are updated throughout this phase in order to reduce loss and gain knowledge.

During the processing phase, the obtained pictures are processed and scaled to match the pre-trained model's first layer. So, all the entered images have been resized for processing. After that, the characteristics of each class are retrieved directly on the fully connected layers using learning-based pre-trained models. They are commonly used as picture feature representations during the retraining of the pre-trained classifiers. CNN features are successfully extracted from picture patches. Ultimately, the learning models developed are used to categorize the sample image.

C. Testing Stage

A test picture is used to examine the scheme in order to assess the model's functionality. The test pictures are handled and downsized to EfficentNet and DenseNet 224x224 dimensions. After that, a picture is passed onto a deep learning model, which will categorize the image. Once trained, deep-learning models are only employed to extract picture characteristics. As a result, CNNs collect image features from picture patches and maximize pooling layer output. The photos are then categorized using the learned classifiers produced during the training stage. Finally, the user is given the final result as a class of the input image.

D. The CNN-based Classification Models

Nowadays, Transfer Learning algorithms have expedited the advancements in Machine Vision, particularly in the area of picture recognition functions. Even though a significant amount of images in the dataset and testing minimizes computational power have been obtained, it often needs multiple cycles. Transfer learning thereby helps scholars to employ a pre-trained model (such as EfficientNet and DenseNet) that has been adopted to solve a classification process with a big dataset. Retraining a model using a dataset consumes less time and more computational resources than training the neural network from scratch in the absence of transfer learning.

1) EfficientNet

EfficentNet[19] is an efficient network that has many convolutional neural layers as shown below in (Fig. 3).

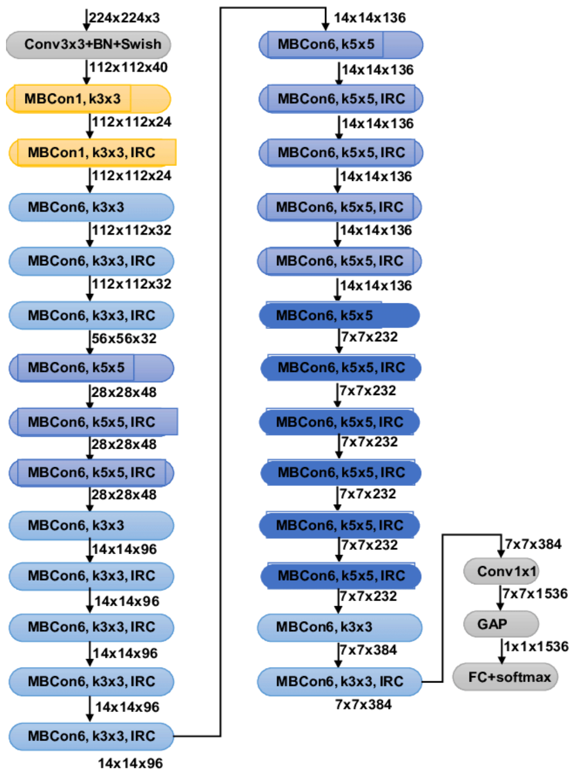

Fig. 3. The architecture of EfficientNetB3 [19].

The preceding architecture shows the layers of one of the Efficient pre-trained model families (EfficientNetB3). It has many convolution layers that extract the feature map of the input images to perform the classification task.

2) DenseNet

According to the new article [20], CNN could be significantly deeper, and more sophisticated to be more effective in learning if the linkages connect the input layer to the near output ones. From article [20], we learned that researchers used a deeper and more sophisticated network to incorporate the vast state-of-the-art network called (DenseNet)[20]. Unlike in L-links, in standard L-layered convolutional networks, DenseNet, features L(L+1)/2 deeply links one layer to the following layers. Every layer's outputs appears to represent the function maps of all preceding layers, and the feature maps of each of the following layers are anticipated (see Fig. 4).

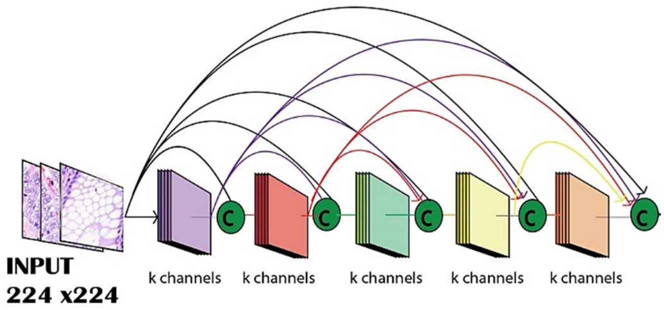

Fig. 4. DenseNet layers in each Dense Block.

III. RESULTS AND DISCUSSION

The study began with a binary classifier for colon tissues. The reported loss rate of DenseNet121 and DenseNet201 is 0.061, and 0.056 respectively. EfficientNet models, however, obtained the best loss rate during the training with 0.00009 as anticipated in Figure 5 (Fig. 5).

Fig. 5. Training Loss of EfficientNet and DenseNet models.

The figure above depicts EfficientNet's ability to be trained efficiently. The training loss of EfficientNet models outperformed DenseNet architectures in terms of training loss. Obviously, as shown in Figure (5), the DenseNet201 obtained a slightly better loss than DenseNet121. From among EfficientNet models, EfficientNetB1 started with the least loss in the 1st epoch, with about 0.1073, and ended up with approximately 0.00009, which is also achieved by other EffientNet models. Consequently, the recognition rate increases in terms of training accuracy as seen in the picture below (Fig.6).

Fig. 6. The Training Accuracy of EfficientNet and DenseNet models.

The above figure shows better detection of colon cancer during the training stage using EfficientsNet than using DenseNet pre-trained models. In the eighth epochs, all EfficientNet models (EfficientNetB7, EfficientNetB2, and EfficientNetB1) achieved a high training accuracy ranging between 99.99% and 100%.

In Fig. 7, the validation loss is depicted as shown below.

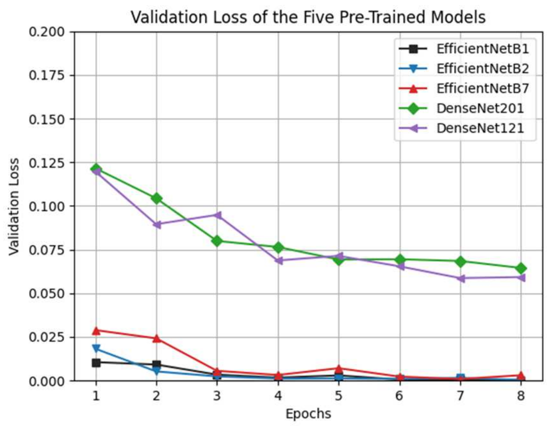

Fig. 7. The validation loss of EfficientNet and DenseNet models.

During the validation stage, EfficientNet models outperformed DenseNet models and obtained better results. The validation loss of EfficientNetB1 and B2 reached 0.00087. Comparatively, the validation loss of DenseNet121 and DenseNet201 reached 0.056 and 0.060, respectively. The validation accuracy during the validation phase is shown in Fig 8 below.

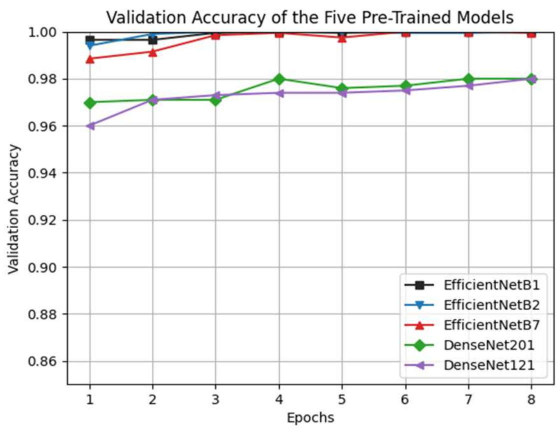

Fig. 8. The validation accuracy of EfficientNet and DenseNet models.

As the preceding figure (Fig. 8) shows, the validation accuracy of EfficientNet, pre-trained models reached the highest degree of accuracy during the validation stage, with around 99.9995%. While the obtained validation accuracy of DeseNet121 and DenseNet201 ended up at 98%. The best testing results obtained are by using EfficientNetB2, which achieved an accuracy of 99.9994%, recall of %99.967, and F1 Score of 99.9977 better than the studies that were mentioned in the literature.

IV. Conclusion And Future Improvement

The present study proposes a methodology for detecting colon cancer by employing pre-trained deep learning models, particularly EfficeintNet for performing the diagnosis tasks. The proposed method can be used to detect colorectal cancer automatically. Furthermore, by an appropriate identification of colon cancer, clinicians can help patients to be effectively handle colon cancer. The technology may offer an optimum and low-cost strategies for detecting and prevent colon cancer at an earlier stage. EfficientNet models are proved to have a high rate of accuracy, and be optimal in detecting colon cancer, particularly, EfficientNetB2, which achieved an accuracy of 99.9994%. Despite the fact that EfficientNetB2 achieved almost optimal results in recognizing colon cancer, findings of this study recommend that the dataset should include more classes. The dataset should not only be limited to two categories of normal and abnormal (colon cancer) images, but there should be also classes of severity grades (the degree of colon cancer severity) included. Moreover, to optimize and improve recognition performance, model phases have to be extended to include segmentation and a grading result for infected malignant tissues.

References

[1] Home. American Cancer Society, Cancer facts & statistics. Available: https://cancerstatisticscenter.cancer.org/?_ga=2.191090925.695772837.1589031645-278983135.1589031645#!/ last accessed (2023, Jan 1, 2023).

[2] M. Tatar and F. J. T. E. J. o. H. E. Tatar, "Colorectal cancer in Turkey: current situation and challenges for the future," vol. 10, no. 1, pp. 99-105, 2010.

[3] Y. LeCun, Y. Bengio, and G. J. n. Hinton, "Deep learning," vol. 521, no. 7553, pp. 436-444, 2015.

[4] A. Sallam, A. E. B. Alawi, and A. Y. Saeed, "Skin Lesions Recognition System Using Various Pre-trained Models," in 2021 1st International Conference on Emerging Smart Technologies and Applications (eSmarTA), 2021, pp. 1-6: IEEE.

[5] A. E. Ba Alawi, A. Y. Saeed, B. Radman, and B. T. Alzekri, "A Comparative Study on Liver Tumor Detection Using CT Images," in International Conference of Reliable Information and Communication Technology, 2021, pp. 129-137: Springer.

[6] M. J. C. i. B. Toğaçar and Medicine, "Disease type detection in lung and colon cancer images using the complement approach of inefficient sets," vol. 137, p. 104827, 2021.

[7] N. Kumar, M. Sharma, V. P. Singh, C. Madan, S. J. B. S. P. Mehandia, and Control, "An empirical study of handcrafted and dense feature extraction techniques for lung and colon cancer classification from histopathological images," vol. 75, p. 103596, 2022.

[8] M. Yildirim, A. J. I. J. o. I. S. Cinar, and Technology, "Classification with respect to colon adenocarcinoma and colon benign tissue of colon histopathological images with a new CNN model: MA_ColonNET," vol. 32, no. 1, pp. 155-162, 2022.

[9] J. N. Kather et al., "Multi-class texture analysis in colorectal cancer histology," vol. 6, no. 1, pp. 1-11, 2016.

[10] A. B. Hamida et al., "Deep learning for colon cancer histopathological images analysis," vol. 136, p. 104730, 2021.

[11] J. Lu et al., "Research on the development and application of a detection platform for colorectal cancer tumor sprouting pathological characteristics based on artificial intelligence," 2021.

[12] H. Chen, H. Zhao, J. Shen, R. Zhou, and Q. Zhou, "Supervised machine learning model for high dimensional gene data in colon cancer detection," in 2015 IEEE International Congress on Big Data, 2015, pp. 134-141: IEEE.

[13] T. Ozawa, S. Ishihara, M. Fujishiro, Y. Kumagai, S. Shichijo, and T. J. T. a. i. g. Tada, "Automated endoscopic detection and classification of colorectal polyps using convolutional neural networks," vol. 13, p. 1756284820910659, 2020.

[14] R. D. Soberanis-Mukul, M. Kayser, A.-M. Zvereva, P. Klare, N. Navab, and S. J. a. e.-p. Albarqouni, "A learning without forgetting approach to incorporate artifact knowledge in polyp localization tasks," p. arXiv: 2002.02883, 2020.

[15] Y. Zeng et al., "Real-time colorectal cancer diagnosis using PR-OCT with deep learning," in Optical Coherence Tomography, 2020, p. OW2E. 5: Optical Society of America.

[16] D. Wang et al., "Afp-net: Realtime anchor-free polyp detection in colonoscopy," in 2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI), 2019, pp. 636-643: IEEE.

[17] E. S. Nadimi et al., "Application of deep learning for autonomous detection and localization of colorectal polyps in wireless colon capsule endoscopy," vol. 81, p. 106531, 2020.

[18] Borkowski AA, Bui MM, Thomas LB, Wilson CP, DeLand LA, Mastorides SM. Lung and Colon Cancer Histopathological Image Dataset (LC25000). arXiv:1912.12142v1 [eess.IV], 2019

[19] H. Alhichri, A. S. Alswayed, Y. Bazi, N. Ammour, and N. A. J. I. a. Alajlan, "Classification of remote sensing images using EfficientNet-B3 CNN model with attention," vol. 9, pp. 14078-14094, 2021.

[20] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 4700-4708