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# Classification and detection of Colon Cancer from histopathological images with CNN model: EfficientNet

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***Abstract*—Colon cancer, a common type of carcinoma affecting the large intestine, impacts over 1.9 million individuals worldwide annually, posing a significant burden on global health. Early detection is crucial, and advancements in medical image classification techniques play an essential role in diagnosis, monitoring, and treatment, as with other types of cancer. However, manually analyzing large sets of medical images entails complexities and potential errors, leading to inaccurate diagnoses and delaying effective treatments. To overcome these challenges, convolutional neural networks (CNNs) were implemented using the EfficientNet method, proving to be viable in detecting colon cancer-related images, achieving a notable accuracy rate of 99.92%. This technological innovation holds promise in identifying the disease in its early stages, potentially revolutionizing treatment effectiveness and patient survival. The successful application of machine learning models in precise medical image classification offers hope for improving healthcare and paving the way for faster and accurate colon cancer diagnosis, with the potential to positively transform the landscape of public health.**

***Index Terms*—Colon cancer, deep learning, CNN, histopathological images.**

## I. Introduction

Colon cancer, also known as colorectal cancer, affects the colon or rectum. The colon absorbs water and nutrients from food, and the rectum is the end of the colon, connected to the anus. This type of cancer usually originates from abnormal growths of tissue called polyps. Not all polyps become cancerous, but some can turn malignant over time. If untreated, these cancerous cells can grow and spread to other parts of the body [1]. The World Health Organization (WHO) estimates that globally, colon cancer affects more than 1.9 million people each year [2]. Symptoms vary and include bowel changes, blood in stool, and fatigue, but in early stages, it can be asymptomatic, underscoring the importance of screening exams [3]. Colon adenocarcinoma, the most common type, originates in glandular cells, and early detection from benign polyps is crucial to prevent its development into cancer [4]. Benign polyps, which are non-cancerous growths in the inner lining of the colon, can turn into adenocarcinoma if not detected and treated properly.

Early detection becomes a key point in effectively preventing and treating colon adenocarcinoma, with colonoscopy being a fundamental method for identifying and removing benign polyps [5]. The integration of histopathological image analysis with convolutional neural networks (CNNs) has enabled precise and early detection of colorectal cancer. Histopathology involves the microscopic study of tissues and cells, providing detailed information about the structure and composition of the tissue [6,7]. Technological advancements in histopathological image analysis have improved the accurate visualization of cellular features associated with colon cancer [8,9]. The application of CNNs in this context has enabled automatic identification and efficient analysis of complex patterns in histopathological images. Moreover, CNNs have enabled the automatic identification of complex patterns in these images, achieving high accuracy in detecting lung and colorectal cancer, such as the presence of cancerous cells, abnormal cellular structures, or morphological changes [10,11,12], reaching an accuracy of 99.6% in identifying lung and colon cancer with transformation methods, such as the use of principal component analysis (PCA). The study proposes the use of EfficientNet for the detection of colon adenocarcinoma and benign colon tissue. Our proposal, compared to previous works with MobileNet and MA ColonNET networks, achieves a superior accuracy of 99.75% [13], which is achieved using scaling coefficients to increase or decrease the depth, width, and resolution of the network proportionally, highlighting its computational efficiency and its ability to balance performance and resources, even in the classification between lung and colon cancers [14]. This approach shows promising results in classification, essential for the development of computer-assisted systems in colon cancer detection. We propose the use of EfficientNet for the detection of colon adenocarcinoma and benign colon tissue, highlighting its computational efficiency and ability to balance performance and resources. The structure of the work is broken down as follows: the EfficientNet architecture used is presented, the methodology employed to implement and train the CNN model is described, the details of data preparation, model architecture, and training parameters are discussed, the experimental results obtained during the training process are presented, including performance metrics such as accuracy and loss, and we conclude with the key findings of the study and suggest possible directions for future research.

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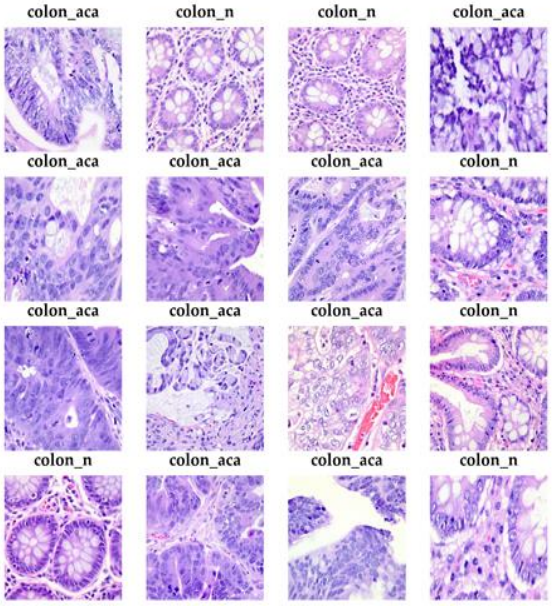


Fig. 1. Visual examples of histopathological images where colon n refers to a normal image and colon aca refers to an image of colon cancer

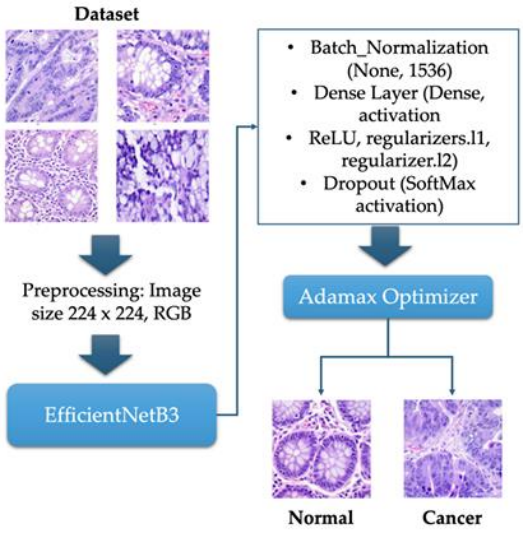


Fig. 2. General architecture proposed

TABLE I
SUMMARY OF CNN EFFICIENT NETB3 PRE-TRAINING MODEL

| Layer (type) | Output Shape | Parameters |
|---|---|---|
| efficientnetb3(Functional) | (None, 1536) | 10783535 |
| Batch normalization | (None ,1536) | 6144 |
| Dense | (None, 256) | 393472 |
| Dropout | (None, 256) | 0 |
| Dense | (None, 2) | 514 |

## II. DEEP LEARNING APPROACH

In this section, the colon cancer dataset used in the study is described, comprising a total of 10,000 images, with 8,000 of them used for model training and the remainder for testing and validation. This is followed by the presentation of the detection method for colon cancer. This paper analyzes the proposed CNN model along with the results showing the highest accuracy obtained.

### *A. Histopathological Image Data*

The dataset corresponds to the histopathological images of lung and colon cancer (LC25000) with 25,000 color images divided into 5 classes. Each class contains 5,000 images of the following histological entities: colon adenocarcinoma, benign colon tissue, lung adenocarcinoma, lung squamous cell carcinoma, and benign lung tissue [15]. Two classes were selected, colon adenocarcinoma and benign colon tissue, all images are 768 x 768 pixels in jpeg file format. Some samples of colon adenocarcinoma and benign colon tissue are shown in Figure 1.

### *B. CNN Model Architecture*

A general schematic of the proposed method with EfficientNetB3 is shown in Figure 2. Initially, the input histopathological images are rescaled to 224 × 224 in RGB format for image preprocessing before being used in the pre-trained CNN, which reduces processing time. The EfficientNetB0 architecture mainly consists of repetitive blocks called ”MBConv blocks” (Mobile Convolutional Blocks). These MBConv blocks are fundamental units that help maintain a balance between model complexity and efficiency. Each MBConv block consists of a sequence of operations, typically:

1. Depthwise Convolution (DW): This convolution is applied to each input channel separately, reducing the number of operations by separating spatial convolution and channel convolution. Then, an activation function, such as ReLU (Rectified Linear Unit), is applied.
2. Pointwise Convolution (PW): Known as 1x1 convolution, it is used to combine information from the input channels processed by the DW convolution. This convolution helps increase dimensionality and learn more complex representations.
3. Skip Connections: These connections allow information to flow directly from the input layers to the later layers, facilitating training and helping to avoid gradient vanishing problems.

Due to its greater complexity, EfficientNetB3 can perform better in computer vision tasks, but it may also require more computational resources and memory compared to smaller versions of EfficientNet [16, 17].

The model is composed of normalization layers with regularizers and “ReLU” activation function, dense layers to reduce dimensionality, a dropout layer for regularization, and finally, a dense output layer for classification with two classes using the ’SoftMax’ activation function.

The Adamax optimizer was used with a learning rate of 0.0001 and “categorical crossentropy” loss. The model was trained for a total of 10 epochs.

Table I summarizes the pre-trained EfficientNetB3 model, indicating the total number of parameters and those that are trainable, with a total of 11,183,665 parameters equivalent to 42.66 MB, of which only 11,093,290 are trainable, equivalent to 42.32 MB. Figure 3 details the activation functions, image

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TABLE II
MODEL TRAINING, ACCURACY, AND LOSSES

| Epoch | Time (sec) | (Losses) | Accuracy |
|---|---|---|---|
| 1 | 2081 | 3.3051 | 0.9808 |
| 2 | 139 | 0.7652 | 0.9933 |
| 3 | 140 | 0.2601 | 0.9987 |
| 4 | 139 | 0.1401 | 0.9983 |
| 5 | 140 | 0.0962 | 0.9996 |
| 6 | 140 | 0.0764 | 0.9996 |
| 7 | 139 | 0.0708 | 0.9991 |
| 8 | 139 | 0.0635 | 0.9996 |
| 9 | 140 | 0.0623 | 0.9992 |
| 10 | 139 | 0.0556 | 1.0000 |

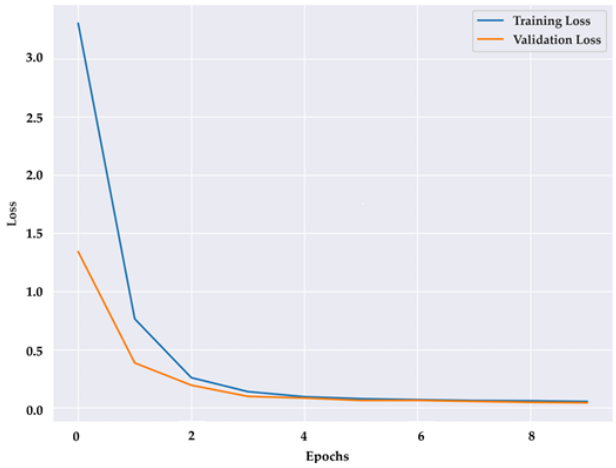


Fig.3. Training loss curves and validation over 10 epochs

TABLE III
CLASSIFICATION REPORT

| Disease | Accuracy | Precision | F1-Score | Recall |
|---|---|---|---|---|
| Colon_n | 1.000 | 1.000 | 1.000 | 1.000 |
| Colon_aca | 1.000 | 1.000 | 1.000 | 1.000 |

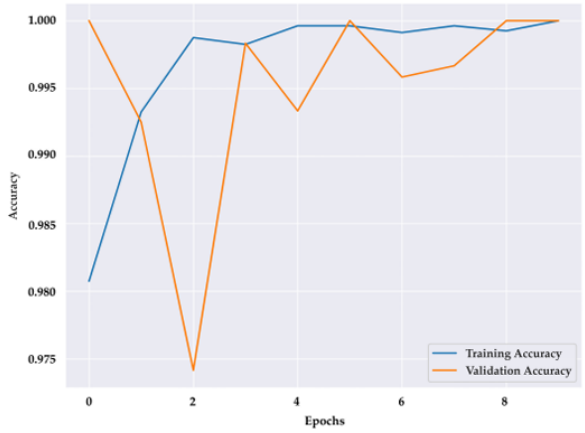


Fig.4. Training accuracy curves and validation over 10 epochs

preprocessing, and optimizers implemented. The model built in Keras consists of several stages:

- Layer1EfficientNetB3: Pre-trained convolutional neural network.
- Layer 2 Batch Normalization: Batch normalization layer.
- Layer3 Dense Layer: Fully connected or dense layer.
- Layer4 Dropout: Dropout regularization layer.
- Layer 5 Final Dense Layer: Reshapes the tensor to "(None,1)" for final classification.

## III. APPLICATION OF EFFICIENTNET

The implemented model was trained using 80%of the available data, while the rest was used for testing, given the dataset's limitation and to avoid possible over fitting during training. The results were implemented in Google Colab Pro, in a hosted environment with a T4 GPU, which is optimized for inference in machine learning applications and is excellent for running pre-trained models in production, offering up to 51GB of system RAM and 15 GB of GPU RAM.

### *A. Experimental Results*

Table II presents the model's performance during training, with accuracy metrics demonstrating the CNN's effectiveness in classifying histopathological images of colon adenocarcinoma and benign tissues. Figure 3 shows the training loss curves and validation over 10 epochs, demonstrating that from epoch number 5, the model avoids overfitting and improves its results by epoch number 10. The accuracy metrics concerning the epochs in Figure 4 show an accuracy exceeding99.5%intraining.

This suggests optimal performance in classifying new histopathological images, demonstrating that the optimizers and regularizers integrated into the CNN architecture improve this aspect. In this work, accuracy is the most relevant performance measure for the classification of the proposed scheme.

Considering the outstanding metrics and results of the Efficient NetB3model, Figure 5 shows the ROC curves in 5a and the Precision-Recall curve in Figure 5b, confirming a value of 1.0. Therefore, Figure6 presents the confusion matrix translated as a binary classification according to True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). A classification of 410 true positives in adenocarcinoma images and 390 true positives in benign tissues is observed.

These results are encouraging, showing no false positives or false negatives. Table III shows the classification report of the data predictions and performance in precision, recall, and f1-score. The definitions are detailed below.

$$precision = \frac{TP}{(TP + FP)}, \tag{1}$$

$$recall = \frac{TP}{(TP + FN)}, \tag{2}$$

$$f1 - score = \frac{TP}{\left(TP + \frac{1}{2}(FP + FN)\right)}. \tag{3}$$

Figure 7 shows the predictions generated by the model when fed with new histopathological images, illustrating the effectiveness of the classification process. The application of deep learning techniques in the field of medical and

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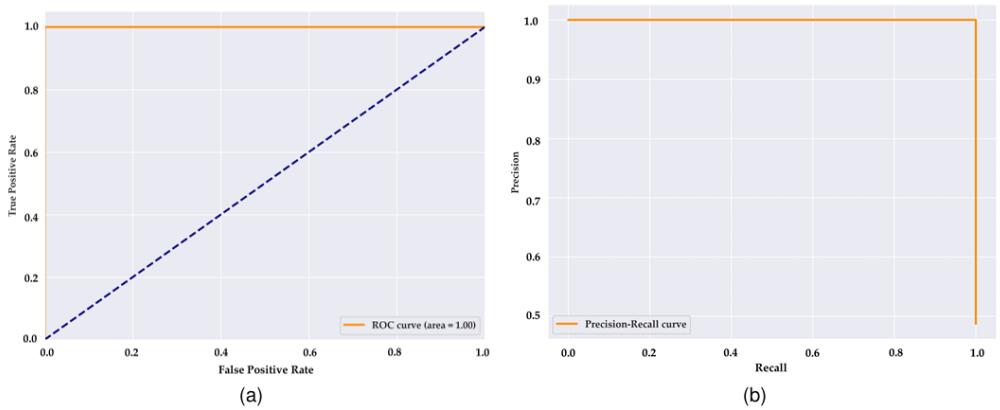


Fig. 5. Binary classifier performance evaluation. (a) Receiver Operating Characteristic (ROC). (b) Precision-Recall Curve

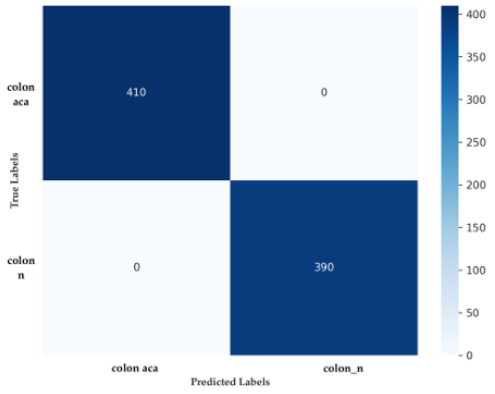


Fig. 6. Predictions obtained in confusion matrix

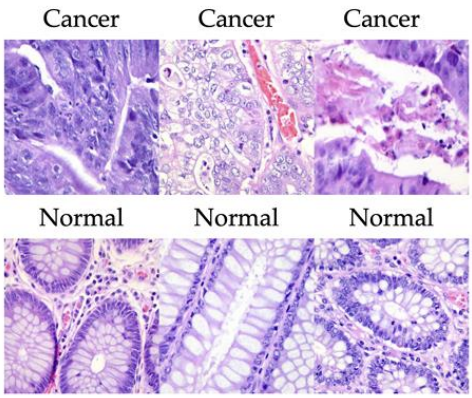


Fig. 7. New predictions obtained with CNN model loaded to Google Colab Pro

pathological diagnosis has shown significant improvements in obtaining results compared to traditional methods.

This could imply a reduction in the work required by experts in the field. The high accuracy achieved of 99.92% underscores the successful development and implementation of an effective model for the early diagnosis of colon cancer.

This accuracy would reduce errors in medical diagnoses, ensuring the feasibility of implementing this algorithm in a pre-diagnostic system accessible to non-specialized professionals.

## IV. Conclusions

This study has made a significant contribution by successfully implementing pre-trained models for the accurate classification of histopathological images in colon cancer detection using CNN. The results obtained show an impressive accuracy of 99.92%, reflecting the robustness and efficiency of deep learning models. This application becomes crucial when the pathologist needs to validate an accurate diagnosis. However, the application of this model is limited to the LC25000 dataset. Therefore, as a proposal for future work, it is suggested to apply the CNN to different datasets available from the National Cancer Institute GDC Data Portal or CIP Cancer Imaging Program, specifically to images related colon adenocarcinoma tissue. This will allow validating the model with diverse datasets to ensure its generalization. The combination of detailed information obtained from histopathological images and the advanced analysis capabilities of CNNs has increased accuracy in the early detection of colon adenocarcinoma. This synergy between technology and medicine promises to continue improving diagnostic strategies, facilitating earlier and more effective intervention in the fight against colon cancer.

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