Enhancing Deep Learning-Based Models for Early Detection of Colon Cancer

Eman A. Elatrash, Naglaa E. Ghannam, Mervat S. Zaki, Rania Salah El-Sayed

Abstract— **Colorectal cancer (CRC) ranks as the third most serious cancer worldwide and is a major global health concern. It contributes significantly to illness and death globally, underscoring the urgent need for enhanced prevention and treatment strategies. The early detection of colorectal cancer is crucial for supporting clinicians' decision-making and reducing their workload. In addition, early detection is crucial for improving the outcomes for CRC patients and can significantly reduce the treatment costs, as this disease is often identified at a late stage.**

The proposed model differentiates between normal and damaged tissues by using the discrete wavelet transform (DWT) for feature extraction, leveraging the resulting coefficients to describe the image. Additionally, convolutional neural network (CNN) architectures, along with image patches and preprocessing, are frequently and widely used. The integration of these two strategies has demonstrated superior effectiveness and efficiency in classification results. Furthermore, the use of DWT significantly reduces training times compared to models that do not employ this technique, highlighting its importance for resource efficiency.This approach allows medical professionals to establish an automated and reliable system for identifying different forms of colon cancer. The model was implemented and evaluated on two datasets of colon images, serving as test beds to demonstrate its capability in accurately analyzing cancerous tissues. After comparing our results with those of related studies, we achieved the highest average accuracy.

Index Terms— **Deep Neural Network, Discrete Wavelet Transform, Convolutional Neural Network, Colorectal Cancer, Feature Extraction**

I. INTRODUCTION

COLORECTAL carcinoma (CRC) is one of the most common diseases and the leading cause of cancer-related deaths worldwide. Current epidemiological data suggest that the survival and health of many patients depends on early diagnosis and differentiation of cancer [1]. According to the world health organization, the likelihood of developing colorectal cancer rises as individuals age, with a higher incidence observed in those over 50 years old. Typical symptoms encompass diarrhea, constipation, blood in the stool, abdominal pain, unexplained weight loss, fatigue, and reduced iron levels. During the initial phases of the disease, many individuals may not experience noticeable symptoms [2].

Colorectal cancer has an annual incidence of 1.2 million cases and a 50% fatality rate, making it the third most prevalent cancer globally and the fourth leading cause of cancer-related deaths [3]. In 2023, an estimated 52,550 individuals are expected to succumb to the CRC disease, comprising 19,550 cases, with 3,750 deaths occurring in individuals below the age of 50 [4].

The diverse locations of colon cancer and its proximity to surrounding organs result in variations in both diagnosis and treatment. In contemporary medical practices, a multidisciplinary approach, including surgery as a central component, is employed. This approach integrates expertise from gastrointestinal, radiology, oncology, and pathology disciplines [5].

The two dyes highlight structural changes in tissues, aiding in the identification and assessment of malignancy presence and extent. Pathologists utilize tissue samples that have been fixed and stained with haematoxylin and eosin (H&E), visually inspecting them under a microscope to diagnose colorectal cancer (CRC) [6],[7].

Prior research [8] utilized t-tests, Mann–Whitney–Wilcoxon tests, neural networks, KNNs, and decision trees to identify the most crucial genes influencing the vital state of patients with colon cancer. The gene expression data for colon cancer genes undergoes two rounds of normalization, followed by the application of unsupervised learning techniques to identify significant patterns.

There are several techniques for classifying colorectal cancer detection methods such as nave bayes, random forests, support vector machines (SVM), gray wolf optimization (GWO)and CNN [9]-[13].

In [9], the introduced model used GWO algorithm to decrease the number of selected features. The system applied the SVM classifier to produce precise cancer classification results. In the case of colon cancer data, the classification accuracy was 95.935%.

In [10], the presented model applied the Naïve Bayes Classifier, relies on a robust independence assumption, and employs a straightforward probabilistic prediction approach by applying Bayes theorem to data sourced from Al-Islam

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Hospital in Bandung, Indonesia. Notably, it achieved a classification accuracy as high as 95.24%. However, the classifier's accuracy diminished in cases where the attributes in the data exhibit interrelatedness, thereby challenging the assumptions of attribute independence.

In [11], they implemented several classification methods include MLP, J48, SMO and naïve bayes on colorectal health data. The experimental findings demonstrated that, in every situation, the MLP approach outperformed the other approaches. The MLP achieved an accuracy of 97%.

Authors in [12] revealed that the random forests model outperformed the LASSO and SVM models in terms of classification when they were compared for the purpose of predicting the disease status of colorectal cancer.

In [13], the presented model utilized a CNN and was evaluated using two publicly available benchmark datasets for colon histopathology images: Stoean, which contains 357 images, and the Kather colorectal histology dataset, comprising 5,000 images. The model achieved accuracies of 97.20% and 91.28%, respectively.

In this paper, we propose an approach consisting of five major contributions:

- Developing and implementing an accurate medical diagnostic support approach specifically designed for detecting colon cancer in images of colon tissue through the utilization of feature extraction and deep learning methods.
- By applying the feature extraction technique of DWT and utilizing the resulting coefficients to represent the images, we facilitate the classification of tissues into normal and injured categories.
- Utilizing a multi-layered CNN for efficient and rapid automatic detection in classification tasks.
- This study demonstrates that utilizing DWT as a feature extraction technique enhances the accuracy of image classification, as evidenced by evaluations on two types of datasets: binary and multi-class.
- Enhancement of training time through the implementation of the proposed model.

Utilizing both stages for the automatic detection of colon images proves to be more precise compared to relying solely on the CNN model. Additionally, the architecture is more compact, leading to decreased training time and lower memory usage.

The remaining sections are organized as follows: section II, our research delves into the realm of similarity studies, thoroughly exploring the advancements and underlying principles that serve as the foundation for our investigation. By building upon this contextual understanding, while section III presents data and the proposed methodology. Section IV presents the results and discussion then conclusion is presented in section V.

II. RELATED WORKS

Early recognition of malignant growth can further develop treatment prospects and increase the endurance of patients. Subsequently, creating proper techniques that can recognize growth subtypes is imperative. Early detection of malignant growth is fundamental for adequate and viable therapy because each disease type requires explicit treatment.

Colorectal disease (CRC) is a serious type of malignant growth with high event and death rates reported in developed nations [14].

To forestall colorectal disease related mortalities, precise discovery, and order of polyps at a treatable stage are basic for moderating the risk of malignant growths. Considering the identification of colonic polyps, colonoscopy is viewed as the standard of care in various reports [15]-[18]. Thus, precise polyp characterization is fundamental to reducing mortality because of colorectal disease as well. AI along with clinical picture handling has been utilized for disease identification and grouping [19]. Early conclusion and appropriate therapy are presently the best ways to lessen the quantity of deaths because of disease [20].

Scientists have utilized both DL and non-DL based learning calculations in practically aspect of a disease determination. Since our work has a place in the lung and colon malignant growth conclusion spaces, we will extravagantly examine the detailed techniques in these two regions. These methodologies shift as far as the sort of pictures utilized, the handling procedures applied to those pictures, the sort of highlights extracted, and the engineering of the ML model utilized for malignant growth recognizable proof [21].

There are existing models for the mechanized characterization of colon polyps. Komeda et. al. [22] presented a model that distinguishes polyps into two kinds, i.e., adenomatous, and non-adenomatous. The author’s dataset incorporates 1,200 adenomatous and 600 non-adenomatous pictures that were taken from a computerized video of real clinical assessments.

In 2020, Suresh and Mohan [23] presented an approach to automatically extracting the self-learned features using an end-to-end learning CNN. In their research, the authors used an architecture with eight layers based on 3-CNN and 3-subsampling. Images used in their study were acquired from the lung image database consortium and infectious disease research institute. The classification accuracy achieved was 93.9%. In addition, the authors presented another approach based on generative adversarial networks (GANs) with a classification accuracy of 93.4%.

Toğaçar [24] presented a model and optimization method that were used for the classification of lung and colon cancers images. The author used a dataset that contains five classes, two for colon malignant growth and three for cellular breakdown in the lungs. The DarkNet-19 model was used as a deep learning model, and SVM was used as a classifier. The methodology achieved an accuracy rate of 99.69%.

In 2022, Ahmed S. Sakr et al. [25] presented paper mainly aims to detect colon cancer from the analysis of histopathological images. Initially, the input histopathological images are normalized before feeding them into their CNN model with different batches and different layers and then selected the best performance architecture to be their model. The selected model consists of 12 layers with total parameters of 4,063,138 with a classification accuracy of 99.5%.

Yildirim and Cinar [26], introduced a strategy based on CNN to recognize colon malignant growth images. They utilized a 45-layer model in a model called MA_ColonNET to group colon diseases. They achieved a 99.75% exactness rate, demonstrating that the introduced approach can identify colon malignant growth prior to treatment.

In 2021, Mehedi Masud et al. [27] inscribed a classification framework to differentiate among five types of lung and colon tissues (two benign and three malignant) by analyzing their histopathological images. The author's model consists of 7 layers. The acquired results show that it can identify cancer tissues with a maximum of 96.33% accuracy.

In [28], the authors used ML algorithms and feature selection techniques to detect colon cancer based on a random forest classifier. The authors model used mean decrease gini and mean decrease accuracy as feature selection approaches. Subsequently Random Forest as classifier. The achieved prediction accuracy 95.161%.

In [29], presented a feature selection approach for Colon cancer detection based on K-means clustering and the modified harmony search algorithm. The others model reported a classification accuracy of up to 94.36%.

In [30], the ResNet50V2 model was utilized by the authors to enhance the CNN model's efficancy and accelerate the computation time for precise and timely identification of tomato plant leaf disease. The model was assessed using the Plant Village dataset, yielding superior results in terms of accuracy value, approximately 99.75%.

In [31], deep convolutional neural networks are highly effective at identifying and classifying images. In this research, to enhance the use of CCTV in managing drug-related issues, the authors have combined face detection, GoogleNet, data augmentation, and transfer learning technologies to develop a distinctive facial image identification framework. This system is designed to differentiate between drug users and non-users. The model achieved an overall classification accuracy of 87.32%, with a high classification accuracy specifically noted at 87.14%, as shown by the results.

Table I illustrates comparative analyses of deep learning and machine learning methodologies applied to colon datasets for the purpose of detecting and classifying ColonCancer.

III. DATA AND METHODOLOGY

In this section, we present the steps of the proposed model designed for detecting colorectal carcinoma. The collected images undergo preprocessing and serve as inputs to the proposed model. The architectural representation of the model is depicted in Figure 1. Further details about the proposed approach are expounded upon in the subsequent subsections.

A. Dataset Description

This study was conducted using two datasets as testbeds. The first dataset related to lung and colon cancer, named LC25000 [36]. The dataset, consisting of 25,000 images and they were categorized into two groups for colon cancer and three groups for lung cancer. The dataset is designed to be balanced, with an equal distribution of 5,000 photos per type of colon cancer) after using the augmentor package. The images are applied among the two types equally of colon cancer, meaning the dataset is balanced, and each type contains 5000 images. These types are colon_aca (Adenocarcinoma) and colon_n (Benign Tissue).

TABEL I.
SUMMARY OF DIFFERENT MODELS ON COLON DATASETS

Method	Main objective	Dataset	ML/DL	Performance
Mohamed Loey Ramadan AbdElNabi et. al.[9]	early diagnosis of cancer based on gene expression	Skewed cancer gene expression datasets	IG + GWO + SVM	95.935%
Komeda et. al. [22]	Colorectal polyp classification.	Colonoscopy	CNN-CAD	0.751
Ahmed S. Sakr et. al. [25]	Colon cancer detection	histopathological images	CNN	99.50%
Mehedi et. al. [27]	Identifying various types of lung and colon cancers.	LC25000 dataset	CNN	96.33%
A. S. M. Shafi et. al. [28]	analyze and predicts colon cancer data	Microarray dataset	Random forest	95.161%
Jin Hee Bae et. al. [29]	classifying colorectal cancer	Dataset Princeton University Gene Expression Project	K-means clustering	94.36%
Murad Al-Rajab et. al. [32]	colon cancer classification	Microarray Databases: Dataset1:Notterman Carcinoma Data Dataset2: Alon	SVM NB DT KNN	81.25% 87.50% 93.75% 93.75%
Abdullah S. et. al. [33]	classification of colorectal cancer	Hstopathological imaging data from the pathology laboratory	MDCNN + swarm Algorithm	99.45%
Sushama Tanwar et. al. [34]	classify colorectal polyps from the colonoscopy images	colonoscopy images	CNN	92%
Chen-Ming Hsu et. al. [35]	Detection and Classification for Colorectal Polyp	colonoscopy images	CNN	95.1%
T. E. Anju et al. [41]	Classification of Colorectal Cancer	sample images taken from the NCT-CRC-HE-100K and CRC-VAL-HE-7K databases	VGG16	95.3%

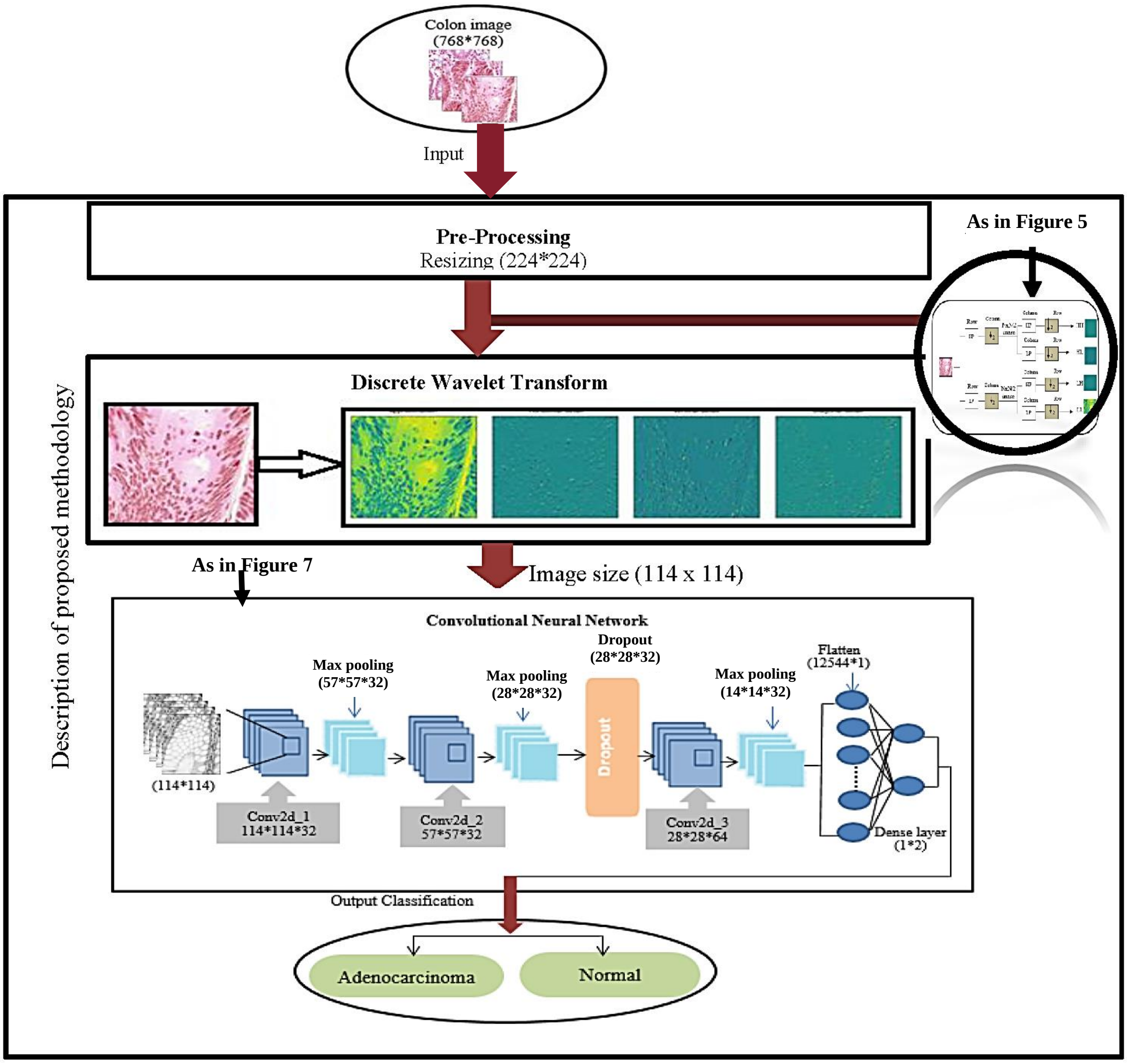


Fig. 1. The proposed model's processing diagram for Colon image

Colon adenocarcinoma represents over 95% of colon cancers, primarily arising from the failure to remove polyps in the large intestine. The remaining two types are benign and lack the propensity to spread to other body parts. However, their accurate identification necessitates thorough verification through biopsy and subsequent removal. Figure 2 displays samples from the colon classes within the LC25000 dataset. Therefore, the dataset was split into training and testing sets as shown in Table II.

(a)

(b)

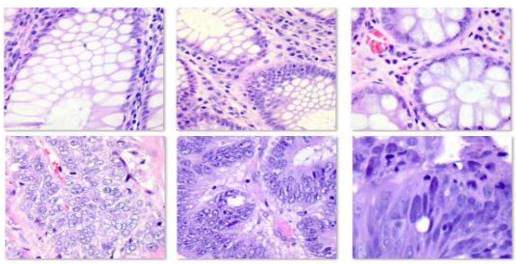


Fig. 2. Samples of the colon classes (a) Normal
(b) Adenocarcinoma

TABLE II.
THE DESCRIPTION OF THE DATASET

Category	Training	Testing
Normal(Benign Tissue)	4507	492
Adenocarcinoma	4491	508
Total	8998	1000

The proposed model was also tested on another dataset, namely the NCT-CRC-HE-100K dataset (https://www.kaggle.com/datasets/imrankhan77/nct-crc-he-100k). The NCT-CRC-HE-100K dataset is a comprehensive resource designed for the analysis of colorectal cancer histopathology. The dataset comprises 100,000 high-resolution images categorized into 9 distinct classes: Adipose (ADI), Debris (DEB), Lymphocytes (LYM), Background (BACK), Mucus (MUC), Smooth Muscle (MUS), Cancer-Associated Stroma (STR), and Colorectal Adenocarcinoma Epithelium (TUM), Normal Colon

Mucosa (NORM). We randomly selected 27,000 images, comprising 3,000 images from each class, and partitioned this dataset into training and testing sets, using 80% for training and 20% for testing. Samples from the nine classes of the dataset are shown in Figure 3. Table III. No of training and testing in each class.

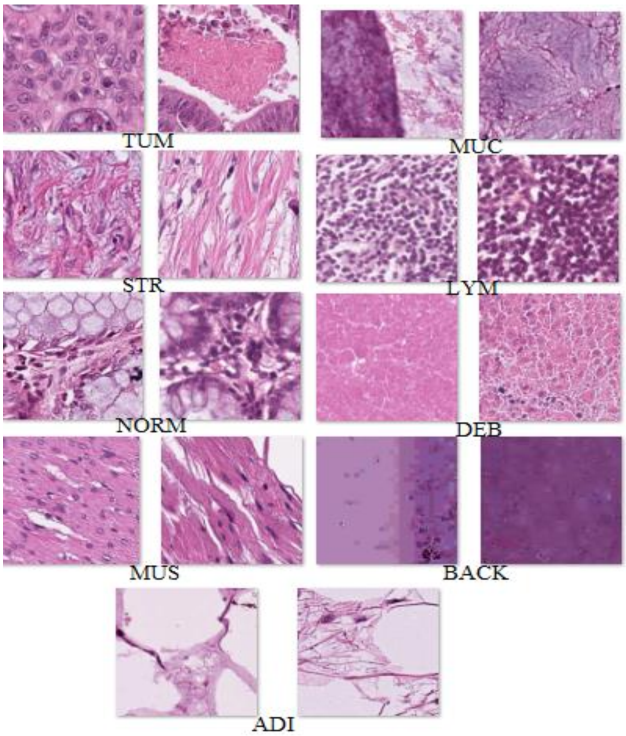


Fig. 3. Samples of the NCT-CRC-HE-100 K Dataset

TABLE III.
DISTRIBUTION OF IMAGES ACROSS CLASSES
FOR THE NCT-CRC-HE-100K DATASET

Class Name	Training	Testing
ADI	2405	595
TUM	2394	606
STR	2398	602
NORM	2401	599
MUS	2383	617
MUC	2406	594
LYM	2413	587
DEB	2406	594
BACK	2394	606
Total	21600	5400

B. Data Pre-Processing

We performed preprocessing operations on the input image through reading the input image in RGB format. Secondly, we resized the cropped image to an optimal size of 224 x 224 pixels. This resizing was necessary because it would result in slower operations, unnecessary power consumption, and increased computation time. Then we reconstructed a database containing images that were all resized to the same dimensions. Figure 4 provides a brief overview of the preprocessing operations applied to some input images extracted from the adapted dataset.

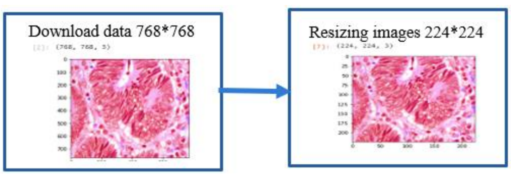


Fig. 4. Preprocessing operation.

C. A discrete wavelet transform (DWT)

A DWT is a method for converting data into wavelet coefficients, which reveals details about the signal's time and frequency distribution [37]. DWT is used in data analysis, compression, and signal and picture processing. Since the discrete wavelet transforms functions well in this domain, it is frequently utilized in the feature extraction stage.

The proposed research employs the technique of data characteristic removal. Initially, features are extracted from processed histopathology images using a 2-dimensional wavelet transform. The Daubechies 4 wavelet filter was utilized for this purpose [38-39]. The discrete wavelet transform divides the image into four sub-bands: HH (diagonal detail wavelet coefficients, while LL signifies low-frequency information, or an approximation coefficient applied to the smoothed image to obtain a smaller-sized approximate image by eliminating unnecessary details. There are many wavelet families like haar, daubechies, symlets, coiflets and biorthogonal.

In the proposed work, we used biorthogonal wavelet due to its possession of the crucial property of linear phase, necessary for signal and image reconstruction. The use of two distinct wavelets, one for decomposition (depicted on the left side) and another for reconstruction (depicted on the right side), as opposed to one, results in interesting properties. We prove that the coefficients in the sub-bands offer valuable insights for textural analysis and differentiation. In this study, we extract the features by computing the mean and standard deviation of the horizontal detail coefficients. Figure 5 shows the process of decomposition, each branch denotes an (N/2) x (N/2) image and makes different contribution during analysis process for N x N image. Sample one-level wavelet decomposed image is shown in Figure 6.

The DWT of f(a,b) of size x,y was calculated by (1),(2) :

$$W_{\varphi}(j_0,x,y)=\frac{1}{\sqrt{xy}}\sum_{a=0}^{x-1}\sum_{b=0}^{y-1}f(a,b)\varphi_{j_{0,x,y}}(a,b) \quad (1)$$

$$w_{\psi}^{t}(j,x,y)=\frac{1}{\sqrt{xy}}\sum_{a=0}^{x-1}\sum_{b=0}^{y-1}f(a,b)\psi_{j,x,y}(a,b) \quad (2)$$

W_{φ} (j_0,x,y) coefficients define an approximation of f(a,b)at scale j0. $w_{\psi}^{t}(j,x,y)$ coefficients add horizontal,vertical and diagonal details for scalej $\leq j_0$.

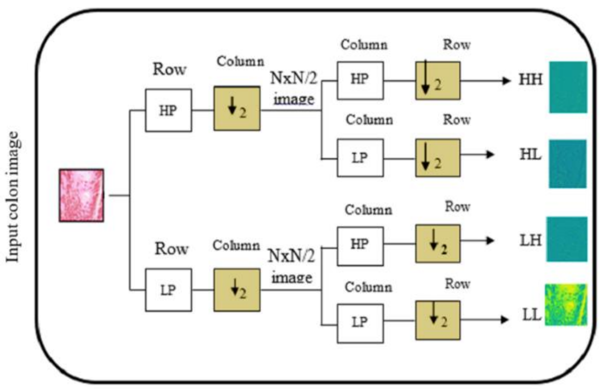


Fig. 5. 2-level Discrete Wavelet Transform (2-DWT).

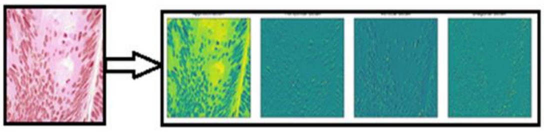


Fig. 6. Appling DWT on Colon image.

D. Convolutional Neural Network

CNN is used to assess the data set to categorize and forecast results based on the training data. Because it can be used to solve a wide range of issues and data sets, it is regarded as one of the most widely used machine learning algorithms [40],[42]. Figure 7 shows the CNN architecture in proposed models that is employed to identify features crucial for determining the image type colon_aca representing adenocarcinoma or colon_n indicating benign tissue. CNN works by approximating images as inputs derived from the DWT, subsequently classifying them into either normal or abnormal categories during the classification phase.

E. Methodology

The proposed approach restructures the data through DWT to establish a threshold for the wavelet coefficient. After subjecting the modified data to an inverse function, the approximate value of the raw data is determined. The highest-ranked wavelet coefficient within the window is then chosen as the predominant feature for that window, following the ranking of wavelet coefficients inside.

As previously mentioned, DWT is employed to reconstruct the approximate image. The wavelet transforms preserves both the frequency and time information of the signal through a variable-sized windowing approach.

Notably, the advantage of the wavelet lies in its adoption of scale rather than frequency. In other words, the DWT generates a time-scale perspective rather than a time frequency view. An effective and powerful way to analyze the data is through the timeline.

In the proposed research, the primary focus is Histopathological Images. It is essential to separately apply the DWT to each dimension. Subsequently, a CNN is applied to 114 × 114 approximate images obtained through DWT.

The architecture illustrated in Table IV consists of CNN layers. The CNN involves the use of a convolutional filter on the input images to create a feature map. The first two convolutional of 32 filters, kernel size (3×3), is employed with a stride of (2, 2) for each step. Following this, the ReLU activation function is applied, and (2x2) Maxpooling is

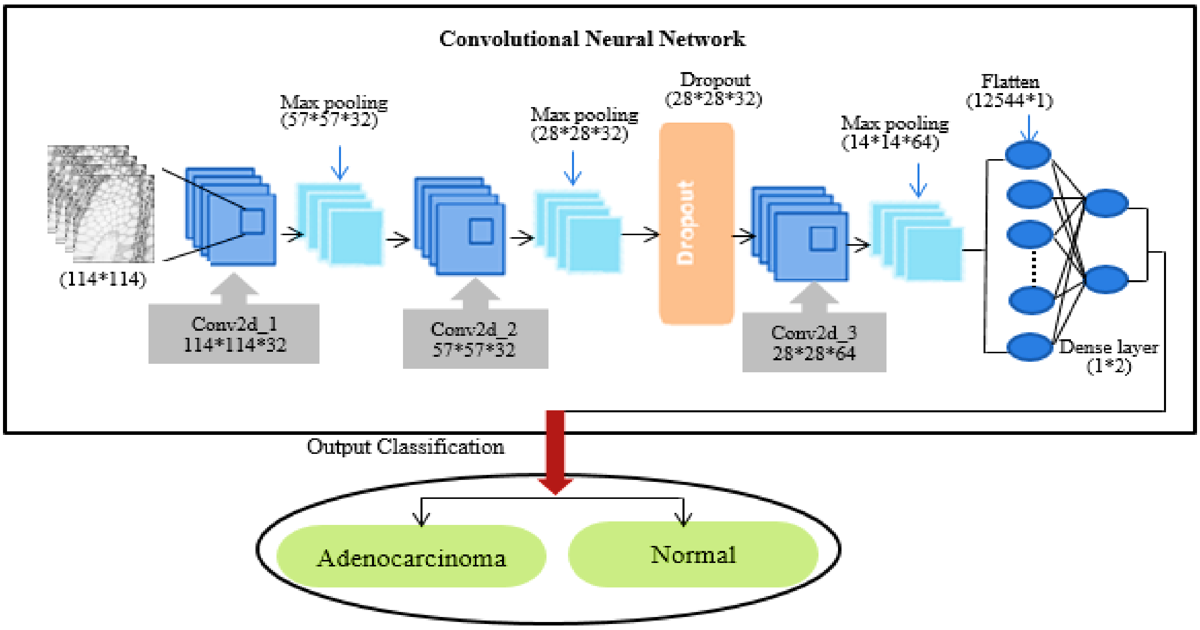


Fig. 7. Convolutional neural network architecture in proposed models for colon image categorization

TABLE. IV
THE SETTING OF CNN ARCHITECTURE

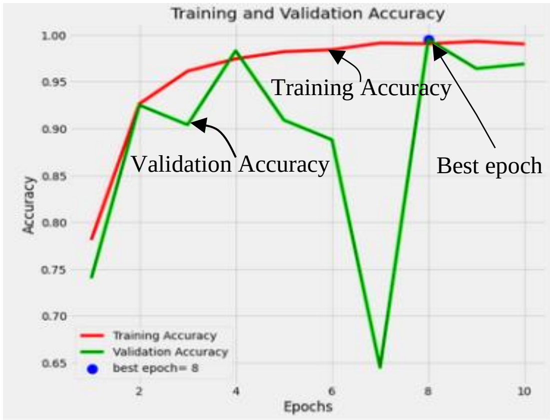
Layer No.	Name	Type	Setting
1	conv2d	Convolutional2D	Filter 32, kernel size 3,padding = 'same', input_shape = (114,114,1)
2	batch_normalization	Batch Normalization	Maintains the mean output close to 0 and the output standard deviation close to 1.
3	activation	Activation	Activation (ReLU)
4	max_pooling2d	MaxPooling2D	pool_size=(2, 2) to reduce the spatial dimensions of the feature maps by a factor of 2 in both the height and width dimensions..
5	conv2d_1	Convolutional2D	Filter 32, kernel size 3
6	activation	Activation	Activation (ReLU)
7	max_pooling2d_1	MaxPooling2D	pool_size=(2, 2) to reduce the spatial dimensions of the feature maps.
8	dropout	Dropout	Rate=0.5
9	conv2d_2	Convolutional	Filter 64, kernel size 3.
10	activation	Activation	Activation (ReLU)
11	max_pooling2d_2	MaxPooling2D	pool_size=(2, 2)
12	flatten	Flatten	Adds a channel dimension and output shape is (batch, 1).
13	dense	Dense	Units=no. of classes, activation('sigmoid')

performed. As a result, images are generated, each with dimensions of 112 × 112.
The third convolutional layer involves the convolution of 64 filters, each kernel size (3×3). These results in a features map consisting of images with dimensions of 57 × 57. At this stage, it was determined that a size of 28 × 28 is suitable for a fully connected layer. The dimensions of 14 × 14 are subsequently transformed into a one-dimensional array, which is then input into a fully connected layer. These features are then processed through the fully connected layer. In the final layer, the classification of Colon images into normal and abnormal categories is achieved using the sigmoid function.

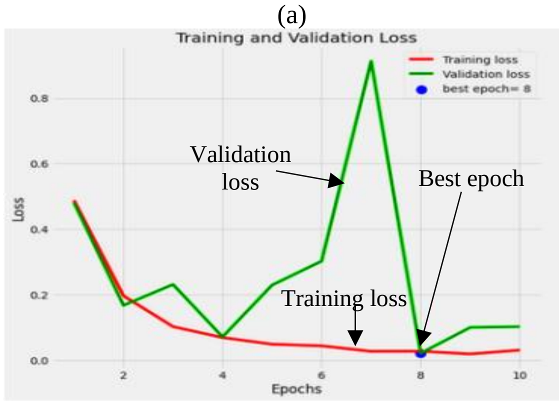
IV. RESULTS AND DISCUSSION

We utilized an Intel Core i7-8565U CPU running at 1.80 GHz (boosting to 1.99 GHz) with 12 GB of RAM to conduct all our experiments. The colon cancer classification was implemented using Jupyter (anaconda3) with python 3 on a 64-bit OS 10 operating system.
In this section, we present the evaluation results of the proposed model for classifying Colon Images using two datasets as testbed. Each dataset was split into training and testing sets as shown in Table II and III. Figures 8 and 9 present the training and validation accuracy (a) and the training and validation loss (b) for the colon dataset using the proposed model on LC25000. These figures illustrate the performance metrics before and after the implementation of DWT, highlighting the best epoch achieved.
We evaluated the performance of the proposed model by training and testing it both with and without DWT. The effectiveness of the proposed model was assessed by computing various evaluation metrics, including accuracy, precision, recall, sensitivity, specificity, G-Mean, and F1-score, as presented in Table V.

The confusion matrix functions as a tabular depiction that facilitates the visual evaluation of a prediction model's performance. Every cell in the confusion matrix shows the number of predictions the model made, differentiating between accurate and inaccurate classifications.
In this work different hyper parameters are applied. Figure 10 and 11 illustrate the confusion matrices for proposed models applying two datasets that employed in this paper when the batch size and learning rate equal to 10 and 0.0005 respectively.
In Figure 10 (a), the confusion matrix for the first LC25000 dataset illustrates that the proposed model utilizing DWT successfully identified 505 images as adenocarcinom, with only 3 misclassifications. For benign tissue, the model accurately classified 488 images, mistakenly labeling 4 images as adenocarcinoma that reported overall accuracy 99.3%
Conversely, in Figure 10 (b), the model without DWT correctly predicted 480 images as adenocarcinom. For benign tissue, it identified 489 images accurately, also misclassifying 3 images. that reported overall accuracy 97%

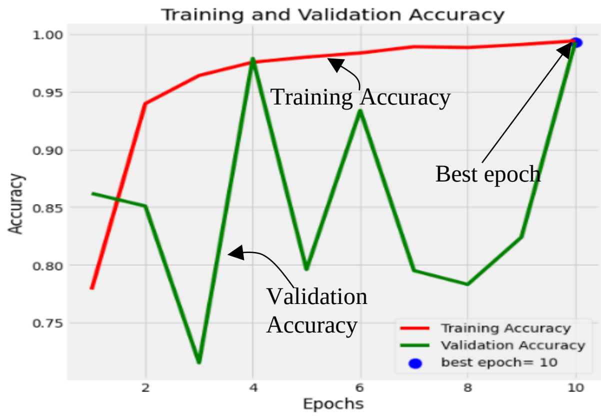


(a)

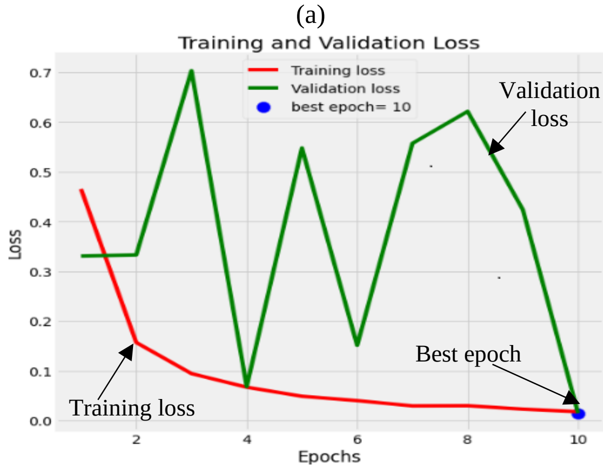


(b)

Fig. 8. Accuracy (a) and Loss (b) of the proposed model on the Colon dataset before applying DWT.



(a)



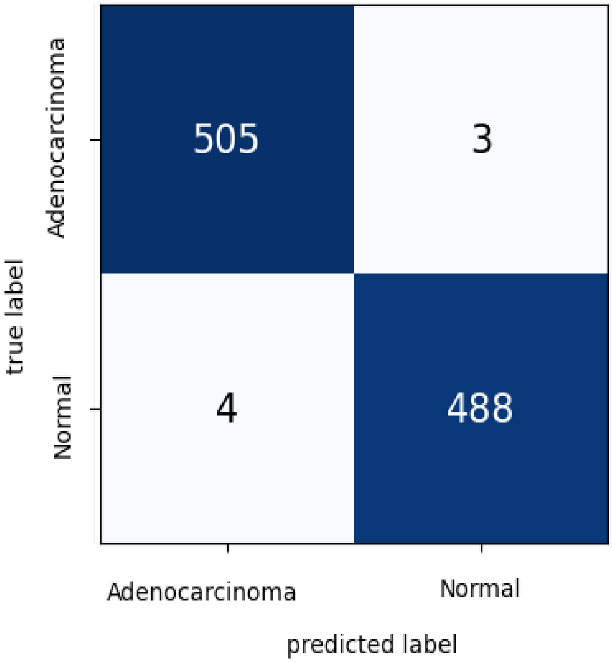
(b)

Fig. 9. Accuracy (a) and Loss (b) of the proposed model on the Colon dataset after applying DWT.

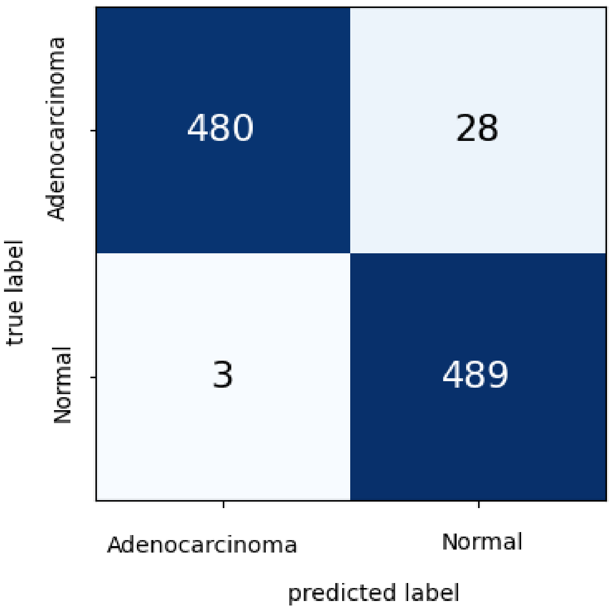
TABLE V.
THE PERFORMANCE OF APPLYING THE PROPOSED MODEL ON TWO DIFFERENT DATASET.

Dataset	No. of Class	Model	Precision%	Sensitivity%	Specificity%	F1score%	recall%	G-Mean%	Accuracy%
LC25000	2	The proposed model without DWT	97	96.9	96.9	97	97	96.9	97
		The proposed model with DWT	99	99.9	99.9	99	99	99.9	99.3
NCT-CRC-HE-100 K	9	The proposed model without DWT	95.75	95.86	99.45	95.54	95.56	97.22	95.54
		The proposed model with DWT	96.37	96.33	99.54	96.33	96.33	97.92	96.33

Figure 11 demonstrates the model's ability to accurately classify each category within the second NCT-CRC-HE-100K dataset. Panel (a) presents the confusion matrix for the proposed model utilizing DWT with overall avarage accuracy 96.33%, while panel (b) displays the confusion matrix for the model applied without DWT on the same dataset with overall avarage accuracy 95.54% .

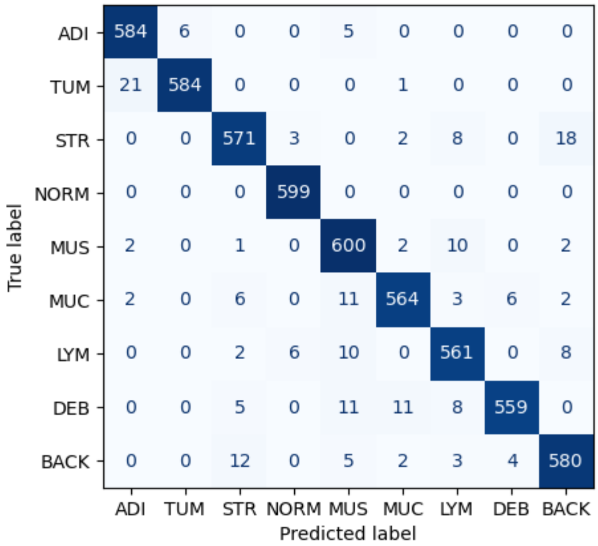


(a)

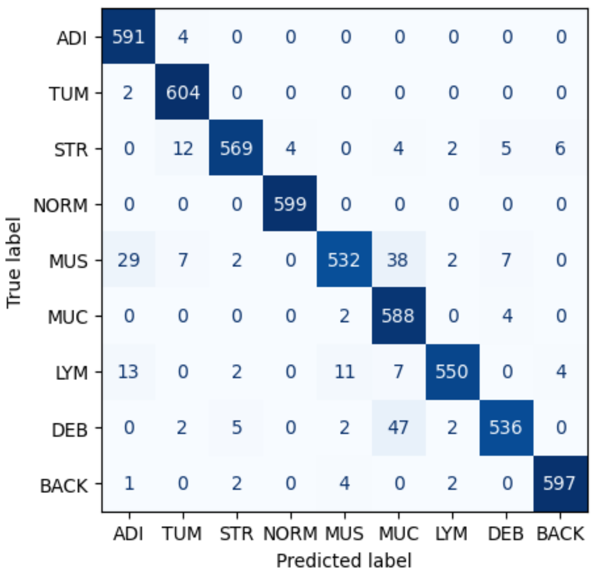


(b)

Fig. 10 Confusion matrix for the proposed model: (a) with DWT; (b) without DWT, on the Colon dataset.



(a)



(b)

Fig. 11 Confusion matrix for the proposed model: (a) with DWT; (b) without DWT, on the NCT-CRC-HE-100 K dataset

On the other hand results presented in Table VI propose that models employing DWT exhibit shorter training times (710.9603s ≈ 11.849 min) compared to those that do not utilize DWT(2884.4132 s ≈ 48.0735min). This advantage can be attributed to several factors: firstly, focused feature learning: By highlighting significant features within the images, DWT allows the model to identify relevant patterns more efficiently. Secondly, dimensionality reduction: The DWT decomposes the image into four sub-bands, as illustrated in Figure 5. This process effectively reduces the input size, contributing to decreased training time. Furthermore, these results highlight how well the models differentiate between cases of "benign tissue" and "adenocarcinoma," with the concatenated model showing especially high accuracy and low misclassification rates.

TABLE VI.
COMPARISON OF TRAINING AND TESTING TIMES FOR PROPOSED MODEL WITH AND WITHOUT DWT

Dataset	Model	Accuracy%	Training time (min)	Testing time (min)
LC25000 dataset	The proposed model without DWT	97	48.0735	0.0694
	The proposed model with DWT	99.3	11.849	0.0215

Table VII. illustrates the performance of the proposed model and comparative results of the different architectures adopted on the LC25000 dataset. The proposed model demonstrated remarkable performance in terms of accuracy. When utilizing feature extraction based on DWT and classification based on Multi-CNN under setting in figure 6 and Table III on the LC25000 dataset as in Table II, the average accuracy achieved was approximately 99%. However, even without the inclusion of DWT was achieved about 97%. their previous work [27], the authors employed a CNN model with a specific architecture consisting of three convolution layers, two maxpooling layers, a batch-normalization layer, and a dropout layer. The reported result for this model on the LC25000 dataset was an accuracy of 96.33%. In another study [28], the architecture of the model incorporates the random forest (RF) algorithm as the classifier.The best reported result achieved using this architecture on the LC25000 dataset was an accuracy of 83%. In [29], the authors utilize an artificial neural network (ANN) as the classifier. The input and hidden layers of the network consist of five nodes, with the sigmoid function used as the activation function. The reported result for this architecture on the LC25000 dataset was an accuracy of 50.3%. A different approach was taken in the research presented in [32], where the model employs a decision tree as the classification algorithm. The reported result for this model on the LC25000 dataset was an accuracy of 70%. Authers in [41] applied learning transfre model VGG-16. The reported result was (93.81%) when applied on dataset as in Table II. A comparison between the suggested approach and earlier studies using the LC25000 dataset is shown in Figure 12. Figure13 depicts the overall accuracy of the proposed model, both without and with the application of DWT, across two different datasets that feature different numbers of classes.

TABLE VII.
COMPARISON OF EARLIER STUDIES WITH THE PROPOSED MODEL USING THE COLON DATASET

References	Model	Accuracy
Mehedi Masud et. al. [27]	CNN	96.33%
A. S. M. Shafi et. al. [28]	Random Forest	83%
Jin Hee Bae et. al. [29]	ANN	50.3%
Murad Al-RajabID et. al. [32]	DT	70%
T. E. Anju et al. [41]	VGG16	93.81%
The proposed model without DWT	CNN	97%
The proposed model with DWT	DWT+ CNN	99.3%

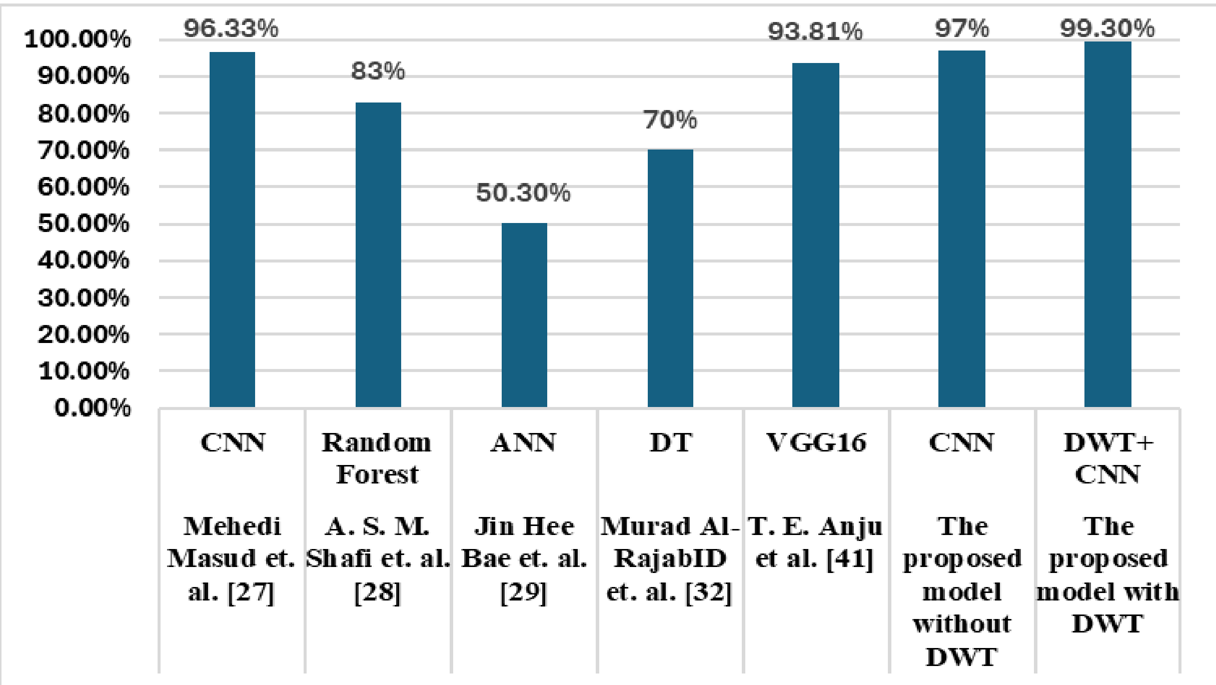


Fig. 12. A comparison between the earlier studies using the colon dataset and the proposed model

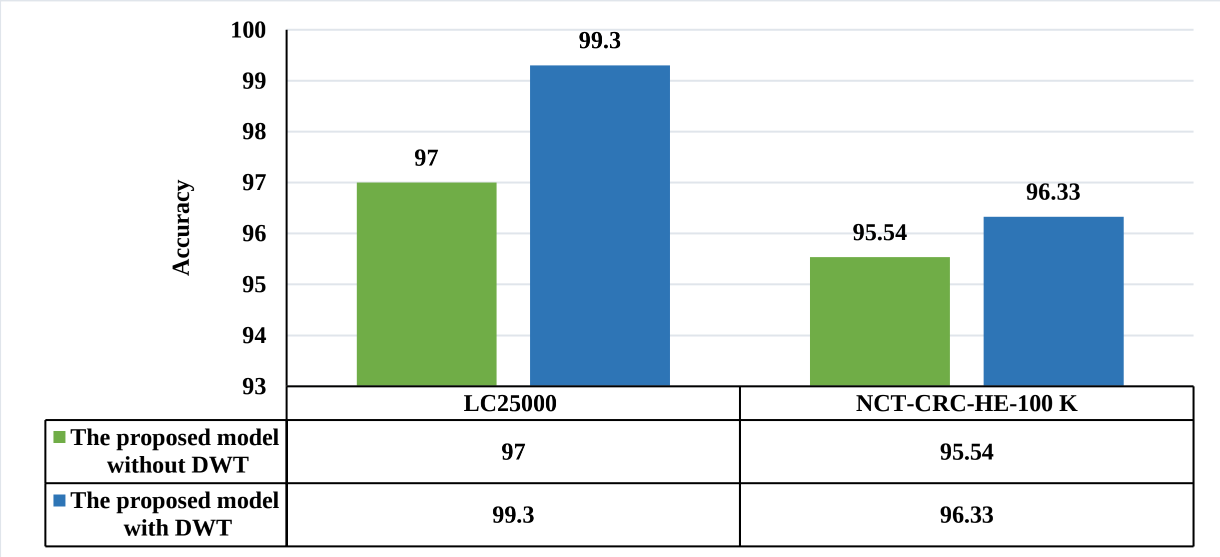


Fig.13 Overall accuracy of the proposed model with and without DWT across two different datasets.

V. CONCLUSION

The proposed methodology in this research involves the integration of a Multi-CNN architecture and DWT for the classification of colon images. When feeding data into a CNN, there is a common issue of image size reduction, which can potentially result in the loss of crucial information. To mitigate this concern and reduce image size while preserving information, the proposed model incorporates the DWT. Wavelets, known for their capability of achieving complete lossless reconstruction of the image, ensure accurate preservation of the original image information. This integration enables an efficient CNN-based colon classification.

The performance of the proposed approach has been thoroughly evaluated using various criteria. The results indicate that the model produces satisfactory outcomes, demonstrating its effectiveness in the classification of colon images.

The primary objective of the image classification model is to surpass existing techniques and provide radiologists with a straightforward tool for decision-making. Notably. the proposed model exhibits outstanding performance while also reducing training time, which is crucial for resource efficiency, achieving 99.3% accuracy with a difference of approximately 36.22 minutes when compared to models that do not utilize DWT, this shows that the measure of how closely the model's predictions match the actual results is high., 99% precision, 99% recall , Precision and recall provide a more nuanced view of the model's performance, especially in cases of imbalanced datasets. In addtion, the suggested model achieved 99.9% Sensitivity, Sensitivity is crucial in applications where missing positive cases (false negatives) is costly, such as in medical diagnoses or fraud detection., 99.9% Specificity , Specificity, also known as the true negative rate, measures the proportion of actual negative instances that the model correctly identifies. It is particularly important in scenarios where false positives are costly. It achieved also 99.9% G-Mean, generalizes meaning that the model performs well in both positive and negative categories. F1- Score is 99% which Indicates a high balance between precision and recall .for LC25000 dataset.

Considering the current system's limitation to binary classification, future efforts aim to extend the model to accommodate multiple classes. Additionally, there is an intention to validate the concept across various modalities. To enhance usability, a web-based interface will be eveloped for radiologists to interact with the system more effectively.

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