A Learninig based Framework for Automatic Detection and Classification of Colon Cancer in Histology Images

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Abstract
One cancer that kills individuals is colorectal cancer, and early identification of this disease can save lives. Since artificial intelligence (AI) has grown in popularity, scientists have started looking at how it may be used to identify colon cancer early. However, as models tend to provide average performance without optimization, the current study on colon cancer diagnosis using deep learning requires improvements. We suggested a framework called Learning based Colon Cancer Detector (LbCCD) to solve this issue. We made it extensible so that we may add to it in the future. With LbCCD, colon cancer may be automatically diagnosed without needing a doctor's knowledge. It may be included into the Clinical Decision Support System (CDSS) of already-available medical software. Based on empirical research, we concluded that the ResNet50 deep learning model is a good fit for detecting colon cancer. We improved ResNet50 by adding more layers through the use of transfer learning. Our algorithm, called Enhanced ResNet for Colon Cancer Detection (ERCCD), makes use of improved ResNet50 to leverage diagnostic accuracy and learn from training samples. In addition, the platform facilitates model modification, fine tuning, and data augmentation to increase cancer detection accuracy even further. Our empirical investigation using datasets related to colon histology showed that ERCCD outperforms other models with an accuracy rate of 93.40%.

Keywords – *Artificial Intelligence, Deep Learning, Colon Cancer Diagnosis, Transfer Learning, Enhanced ResNet50*

1. INTRODUCTION

The Internet of Things facilitates communication by linking several devices to the internet. These days, IoT devices are widely employed in many different applications, such as body sensor networks, smart homes, smart cities, smart grids, and ad hoc networks in cars. The Internet of Things (IoT) refers to the network of interconnected, autonomous gadgets. Information from the actual world is now digitalized thanks to the recent internet-connected IoT gadgets. The term "colon cancer" describes the abnormal growth of large intestine cells that have the potential to harm other body regions [10]. One of the most common types of cancer is colon cancer, which can be brought on by aging, genetics, and an unhealthy lifestyle. Lack of exercise, smoking, poor nutrition, and obesity are other causes of colon cancer [11]. The main signs and symptoms of colon cancer are weight loss, exhaustion, stools, and irregular bowel motions. Furthermore, a benign tumor manifests as a polyp at first before developing into a malignancy [12, 3]. The development of healthy cells on the colon's lining is the primary cause of most cases of colon cancer. A number of variables, including age, gender, ethnicity, socioeconomic status, and smoking habits, may influence the alterations.

Colon cancer refers to the cancer cells that damage the colon, which is the last segment of the digestive system. Despite not being age-specific, colon cancer nonetheless has a significant impact on senior citizens. Typically, it begins as benign, little cell clusters called polyps that form on the colon's internal lobes. Colon cancer is a term used to describe certain polyps that develop on the colon [8]. The primary cause of patient mortality in the industrialized world is colon cancer. Colon cancer is killing more than 500,000 individuals worldwide [13, 4]. Colorectal cancer (CRC), another name for colon cancer, originates in the large intestine's lower section [14, 4]. Generally speaking, cancer cells have more genetic variety than normal cells do, yet malignant tumors display different specific combinations of genetic alterations in different individuals. However, it's possible that cancer is not the source of these noticeable changes, but rather its result. Additional alterations are brought about by the growth of cancer cells, such as the recognition of clinical difficulties and scientific facts. Early cancer detection can thereby improve patient survival and diagnosis rates. Furthermore, the development of diverse approaches can distinguish the tumor into a number of subtypes. Since every type of cancer requires a different therapy, early discovery of the disease is important for treating it at an early stage [2].

To diagnose the illness, a variety of diagnostic techniques have often been used, including ultrasound, magnetic resonance imaging (MRI), computed tomography (CT) scans, biopsies, Positron Emission Tomography (PET) scans, and more [6]. Traditional methods have been used to increase the detection rate since these procedures might yield incorrect results. To identify the different instances that conform to the guaranteed data patterns, the conventional methods developed for recognizing the various illnesses rely on human understanding. These current approaches, however, may have some shortcomings, including the possibility of human mistake, inaccurate identification, labor-intensiveness, time consumption, and stress on the process as a whole. Furthermore, machine learning approaches have been employed by Computer-Aided Diagnosis (CAD) systems to improve illness diagnosis [15, 16, 2]. An description of a few popular techniques for cancer detection is provided below. To determine which genes in the microarray data are impacted, gene selection techniques have been used. The classifier incorporates feature selection techniques to categorize the pertinent genetic component. Furthermore, the feature selection strategies—such as wrapper-based and filter-based approaches—have been divided into two distinct groups. To extract the pertinent characteristics from the actual feature collection, filter-based techniques have been used [19]. Furthermore, the computational complexity and expense of filter-based methods decreased overall efficiency. Similarly, the wrapper-based methods used the concept of a classifier to choose the best answers [17, 18, 3]. The following are our contributions to this publication.

1. We presented the Deep Learning based Colon Cancer Detector (LbCCD) framework.
2. Using improved ResNet50 to learn from training data and improve diagnostic accuracy, we devised an algorithm called Enhanced ResNet for Colon Cancer Detection (ERCCD).
3. We developed a prototype to assess LbCCD and the underlying algorithm ERCCD on datasets related to colon histology and discovered that ERCCD outperforms its predecessors.

This is the arrangement for the remaining section of the task. A review of the literature on colon cancer detection is presented in Section 2, the IoT system model is explained in Section 3, the developed technique is described in Section 4, the findings and discussion of the produced model are shown in Section 5, and the study conclusion is explained in Section 5.

2. RELATED WORK

This section reviews literature on existing methods used for colon cancer detection. Jha et al. [1] Computer vision aids colonoscopy by detecting and segmenting polyps. Benchmarking remains a challenge due to diverse methods. This study benchmarks ColonSegNet on Kvasir-SEG, demonstrating superior speed and performance. Automated polyp identification using deep learning can enhance clinical practices and reduce miss-detection rates. Lange et al. [2] Multimedia research addresses challenging tasks like video analysis for surveillance or medical content. This study proposes effective real-time polyp detection methods, emphasizing GAN-based approaches with promising results. Kiser et al. [3] Technological advances in life sciences enable gathering diverse multimodal data, fostering the development of data-intensive machine learning techniques. This paper surveys applications and compares performances in biological data mining. Jenssen et al. [4] detected colorectal polyps early is crucial for preventing cancer. Advances in deep learning, particularly CNNs, improve detection and segmentation. This work enhances interpretability and uncertainty estimation in polyp segmentation. Liu et al. [5] enhanced skin cancer classification using Bayesian Deep Learning for uncertainty quantification. A dynamic TWDBDL model shows promising accuracy, F1-score, and AUC results.

Jha et al. [6] ResUNet++ enhances colorectal polyp detection through CRF and TTA, exhibiting improved performance across datasets, emphasizing overlooked, smaller, and flat polyps. Zhou et al. [7] Deep learning revolutionized medical imaging, overcoming challenges. Survey explores DL trends in network architecture, label issues, and clinical applications, emphasizing future integration with patient data. Khan et al. [9] proposed a fully automated system for stomach infection diagnosis using deep learning, achieving 98.4% accuracy. Future focus includes reducing computational time. Dlamini et al. [10] AI and machine learning impact healthcare, particularly in oncology through NGS and medical imaging advancements. Challenges persist but show promise.

Li et al. [11] Medical image segmentation faces challenges with imperfect datasets. Solutions address scarce and weak annotations, reviewed for implementation and performance, fostering awareness. Lange et al. [12] The ResUNet++ model enhances colonoscopy polyp segmentation, outperforming U-Net and ResUNet. Achieves high evaluation scores, promising clinical applicability. Laak et al. [13] Stain variation affects CNN performance in pathology. Stain color augmentation and normalization methods are compared. Practical guidelines provided for optimal usage. Deen et al. [14] surveyed the role of Convolutional Neural Networks (CNNs) in medical image analysis, covering classification, segmentation, and detection tasks. Wu et al. [15] introduced Collaborative Unsupervised Domain Adaptation to improve deep learning in medical image diagnosis, addressing label scarcity and noise.

Yang et al. [16] explored AI applications in cancer diagnosis and prognosis, highlighting improved accuracy through machine learning and deep learning. Berre et al. [17] AI's role in gastroenterology and herpetology is evolving for diagnosis, prognosis, and treatment predictions. Challenges include dataset quality and ethical considerations. Sabol et al. [18] introduces an explainable classifier, CFCMC, for histopathological cancer image classification, providing insights into its usability and reliability through clinical trials. Weber et al. [19] focused on deep learning models for colorectal cancer diagnosis and segmentation, achieving high accuracy rates with RESNET and SEGNET models. Coccia [20] explored the growing applications of deep learning in cancer imaging, highlighting its potential impact on diagnosis and treatment.

Tamai et al. [21] A multicenter randomized controlled trial demonstrated that the computer-aided detection (CADe) system, based on deep learning, significantly reduces adenoma miss rates during colonoscopy. The study involved 358 patients, showing a lower miss rate for adenomatous lesions, particularly in the right-sided colon. The CADe system's effectiveness could lead to a reduced incidence of post-colonoscopy colorectal cancer. Picon et al. [22] Early detection of colorectal cancer is crucial for survival. Colonoscopy, assisted by deep learning-based CAD systems, enhances adenoma detection rates. The review analyses methods, datasets, and challenges. Validation and clinical application remain priorities. Ito et al. [23] a dataset of 300 laparoscopic colorectal surgery videos was created, aiding AI in accurate surgical phase, action, and tool recognition. Dou et al. [24] the 3-D RoI-aware U-Net (3-D RU-Net) is proposed for efficient and accurate colorectal cancer segmentation, achieving superior results. Hohn et al. [25] this systematic review evaluates CNN-based approaches for gastrointestinal cancer pathology, highlighting advances, challenges, and the need for clinical validation.

Rong et al. [26] reviewed outlines AI advancements in biomedicine, encompassing disease diagnostics, living assistance, and research, highlighting ongoing progress and potential. Anggia et al. [27] explored ResNet in colorectal cancer detection, with ResNet-50 outperforming ResNet-18 in accuracy, sensitivity, and specificity on varied test sets. Taha et al. [28] introduced a novel approach, using BPSO-DT and CNN, to classify five cancer types based on RNA-Seq data. Achieving 96.90% testing accuracy, it outperforms related works. Altaba et al. [29] Efficient drug repurposing, especially for cancer, requires machine-learning methods and detailed phenotypic studies, integrating various "-omics" data and patient-specific testing. Improved assays are crucial for clinical trial success. Environmental considerations in repurposing drugs for veterinary use must be addressed. Future breakthroughs rely on advancing machine learning and large dataset mining. Personalized phenotypic validation is essential for successful drug development. Roukos et al. [30] Advanced in genomics, transcriptomics, and editing technologies, along with machine learning, offer hope for addressing colorectal cancer challenges. Research transitions to clinical precision medicine for effective treatments. Literature has revealed that there is need for improving CNN models for better performanace in detection of colon cancer.

3. PROPOSED SYSTEM

3.1 Problem Definition

Provided colon caner histology images, developing a deep learning based system for automatic detection of colon cancer is the problem considered.

3.2 Our Framework

Our Deep Learning based Colon Cancer Detector (LbCCD) framework was suggested. We made it extensible so that we may add to it in the future. With LbCCD, colon cancer may be automatically diagnosed without needing a doctor's knowledge. It may be included into the Clinical Decision Support System (CDSS) of already-available medical software. Based on empirical research, we concluded that the ResNet50 deep learning model is a good fit for detecting colon cancer. We improved ResNet50 by adding more layers through the use of transfer learning. Figure 1 depicts the suggested framework's overview.

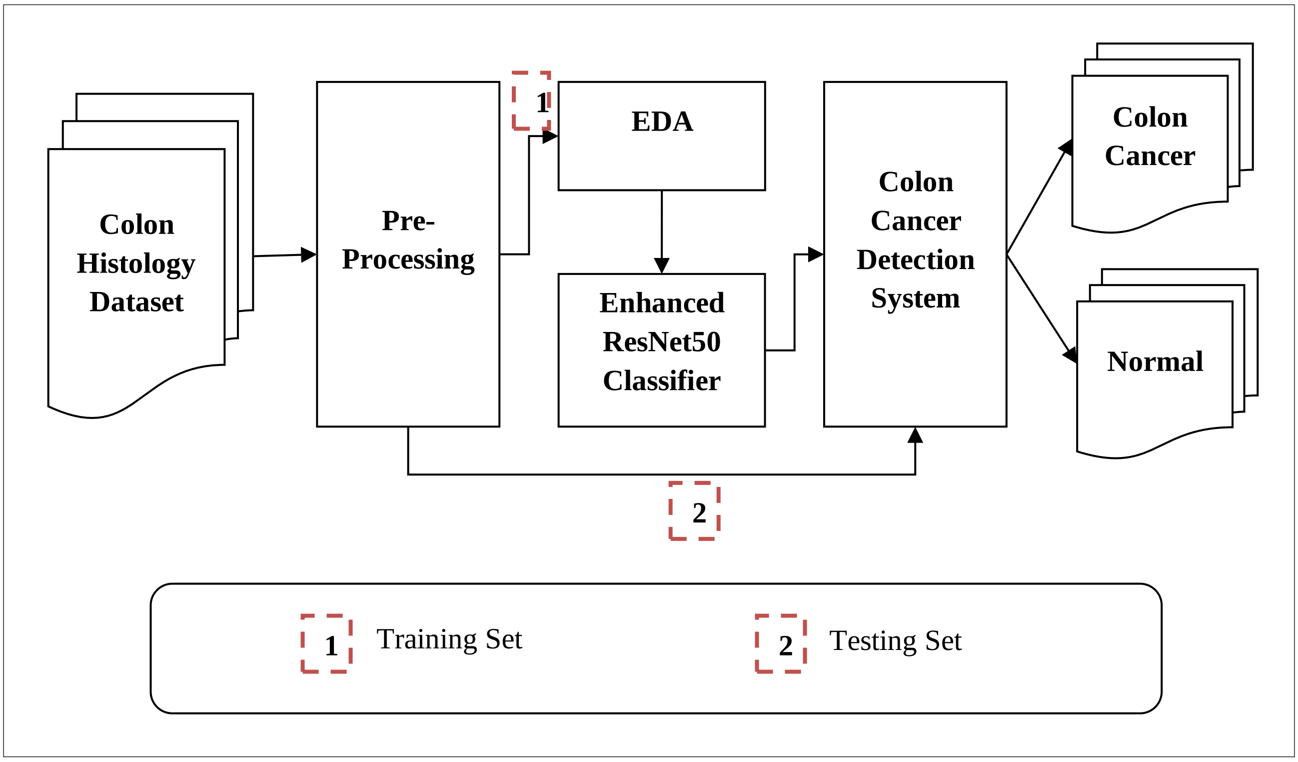

Figure 1: Overview of the proposed framework named Learning based Colon Cancer Detector (LbCCD)

The dataset on colon histology is fed into the system. Following some pre-processing, the data is split into 90% for training and 10% for testing. In order to increase the ResNet50 model's performance in colon cancer detection, we upgraded it with transfer learning. Following training with training samples, the model and its weights are stored. Subsequently, unlabeled test samples are tested using the same model. To aid in the early detection of colon cancer, the framework allows for multi-class categorization. The suggested model's performance may then be evaluated thanks to the framework.

3.3 Enhanced ResNet50 Model

ResNet50 is one of the deep learning models of 50 layers deep. It is CNN variant that is characterized by skip connection. It has two kinds of blocks named identity block and convolution block. Convolutional block has output dimensions that are larger than that of inputs. With respect to identity block input and output dimensions are same. In both of the bocks 1x1 convolutional layer is present in the beginning of the bock. It has bottleneck approach which has potential to reduce number of parameters.

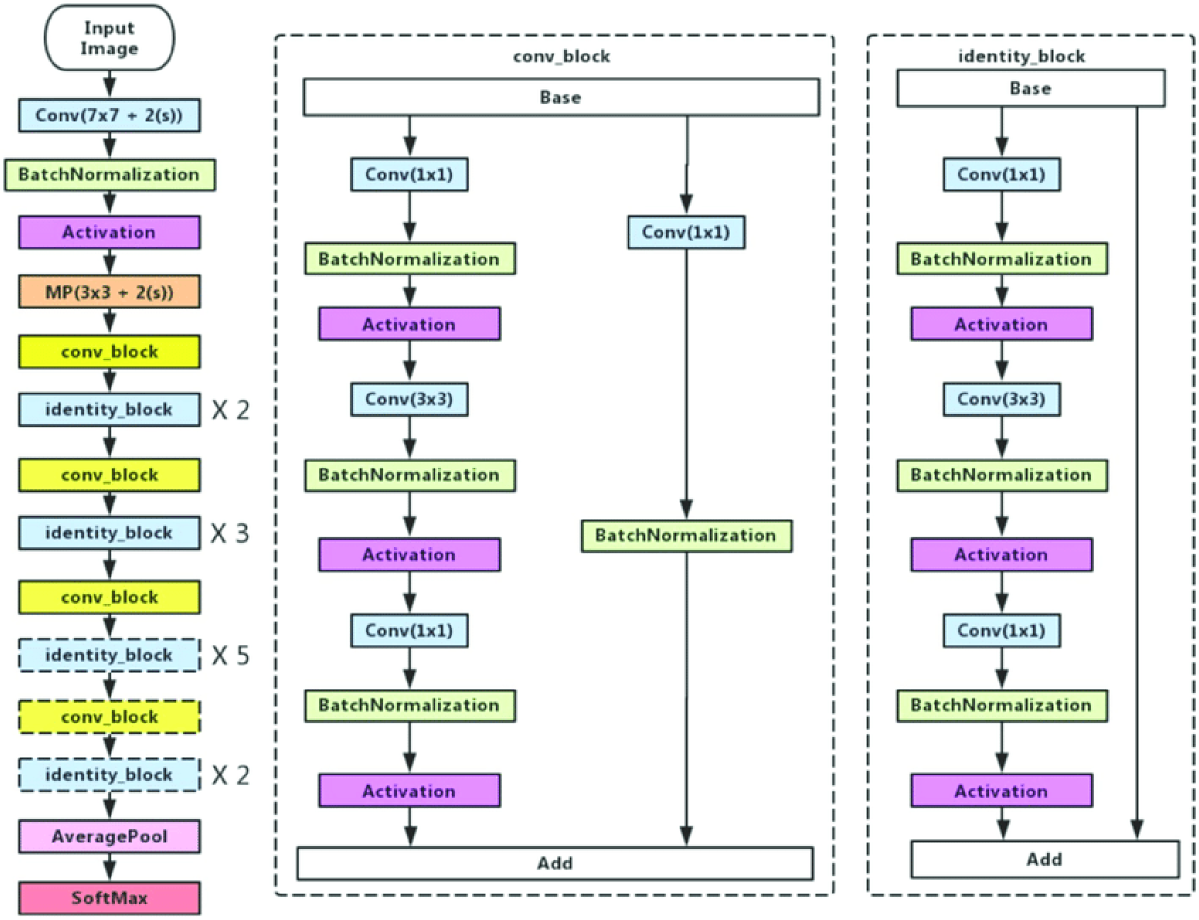

Figure 2: Illustrates more technical details of the enhanced ResNet50 architecture

Figure 2 shows enhanced architecture of ResNet50. Some blocks are shown with dottedlines that indicate enhancements in ResNet50. It has residual learning process which is expressed in the form of Eq. 1.

$$y= F(x, \{ W_i \}) + x. \quad (1)$$

The variablels x and y denote input and output vectors and the concept of residual mapping is expressed as F(x, $\{ W_i \}$). The equation also reflects shortcut connection that reduces number of parameters leading to less computational complexity. The optimized approach for improving performance is expressed as in Eq. 2.

$$y= F(x, \{ W_i \}) + W_s x. \quad (2)$$

where W_s denotes project which is found appropriate in case of same input and output dimensions. This can make flexible residual function and F(x, $\{ W_i \}$) denotes many convolutional layers in the network.

3.1 Improving Quality of Data

In the process of supervised learning, data quality is very important. Pre-processing is applied to the entire dataset gathered from reference [31]. For ease of processing, the histology pictures and their labels are kept as arrays. Following then, 90% of the data is used for training and 10% for testing. Subsequently, the labels undergo conversion into one-hot tensors, enabling effortless processing of class probabilities and model prediction. Every one of the eight classes listed in Table 1 is present in both the training and testing samples.

3.2 Enhanced ResNet50 Model with Transfor Learning

An empirical evaluation of the original ResNet50 model's efficacy in detecting colon cancer was conducted. Through empirical research, we have discovered that ResNet50 has to be further refined and trained from scratch in order to achieve the required accuracy in colon cancer diagnosis. The improved ResNet50 model with transfer learning is displayed in Figure 3.

Layer (type)	Output Shape	Param #
resnet50 (Functional)	(None, 7, 7, 2048)	23587712
flatten (Flatten)	(None, 100352)	0
dense (Dense)	(None, 1024)	102761472
dropout (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 512)	524800
dropout_1 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 9)	4617

Total params: 126,878,601
Trainable params: 103,290,889
Non-trainable params: 23,587,712

Figure 3: Enhanced ResNet50 model with transfer learning

Four further layers are added to the original ResNet50 model: a flatten layer, dense layer, a dropout, dense layer, dropout and dense layer. It is discovered that the improved ResNet50 model is more effective than the first one. To increase the accuracy of the colon cancer diagnosis, we further enhanced the model using data augmentation, the RMSProp optimizer, learning rate, and SGD optimizer fine-tuning.

3.3 Proposed Algorithm

Our suggested system, called Enhanced ResNet for Colon Cancer Detection (ERCCD), makes use of improved ResNet50 to leverage diagnostic accuracy and learn from training samples. The algorithm facilitates the augmentation of data, model improvement, and fine tuning to enhance the precision of cancer diagnosis.

Algorithm: Enhanced ResNet for Colon Cancer Detection (ERCCD)

Input: Colon cancer histology dataset ***D***

Output: Colon cancer detection results R, performanace statistics ***P***

1. Begin
2. ***D'***← DataPreProcess(***D***)
3. (***T1***, ***T2***)←SplitData(***D'***)
4. ***T1***←OneHotEncoding(***T1***)
5. ***T1***←DataAugmentation(***T1***)
6. Build ResNet50 model with transfer learning
7. Compile the model
8. ***m***←TrainResNet50 Model(***T1***)
9. ***R***←TestResNet50 Model(***T2***)
10. ***P***←EvaluatePerformance(***R***)
11. Print ***R***
12. Print ***P***
13. End

Algorithm 1: Enhanced ResNet for Colon Cancer Detection (ERCCD)

Colon cancer histology dataset D is the input for Algorithm 1, which produces performance statistics P and colon cancer detection results R. The provided dataset is pre-processed in step 2, where labels and pictures are saved as arrays. The dataset D' is then divided into two sets: T1, the training set, which contains 90% of the data, and T2, the testing set, which contains 10% of the data. Afterwards, T1 labels are transformed into one-hot encoders in step 4. Data augmentation using various operations, including rotation, zoom, shift, and flip, considerably enhances the quality of the training set (step 5). Step 6 involves configuring transfer learning and building the ResNet50 model. Step 7 involves compiling the model, and Step 8 involves training the ResNet50 model with T1. The model that has been learnt is stored for further use. Subsequently, the deep learning model that has been kept is utilized whenever fresh samples require testing. Step 9 involves classifying colon cancer using the model. As seen in Table 1, there are eight class labels in this multi-class categorization. As seen in step 10, the testing procedure produced a confusion matrix and findings for the detection of colon cancer. Step 11 evaluates the suggested model's performance as it applies to the algorithm.

4. RESULTS AND DISCUSSION

This section offers comprehensive descriptions of the dataset's use, analytic findings, experimental setup, and experimental outcomes.

5.1 Experimental setup

A Python tool is used to investigate the new approach in relation to assessment metrics.

5.2 Dataset description

Patient histology samples are included in the dataset utilized for the research. A selection of histology photos related to human colon cancer are included in the dataset. The source of it is [31].

5.3 Performance metrics

The three assessment metrics for the developed colon cancer detection method are testing sensitivity, specificity, and accuracy, which are discussed below.

Testing accuracy: Testing accuracy, as defined by Eq. 1, is the ratio of patients who are really recognized to all patients.

$$a = \frac{R_P + R_N}{R_P + R_N + S_P + S_N} \quad (1)$$

where, R_P signifies true positive, R_N symbolizes true negative, S_P designates false positive, and S_N signifies false negatives.

5.4 Results

The experiment findings are shown in this part along with an explanation of the observations. It sheds information on colon cancer detection outcomes as well as performance comparison findings between the Enhanced ResNet50 model and its variations.

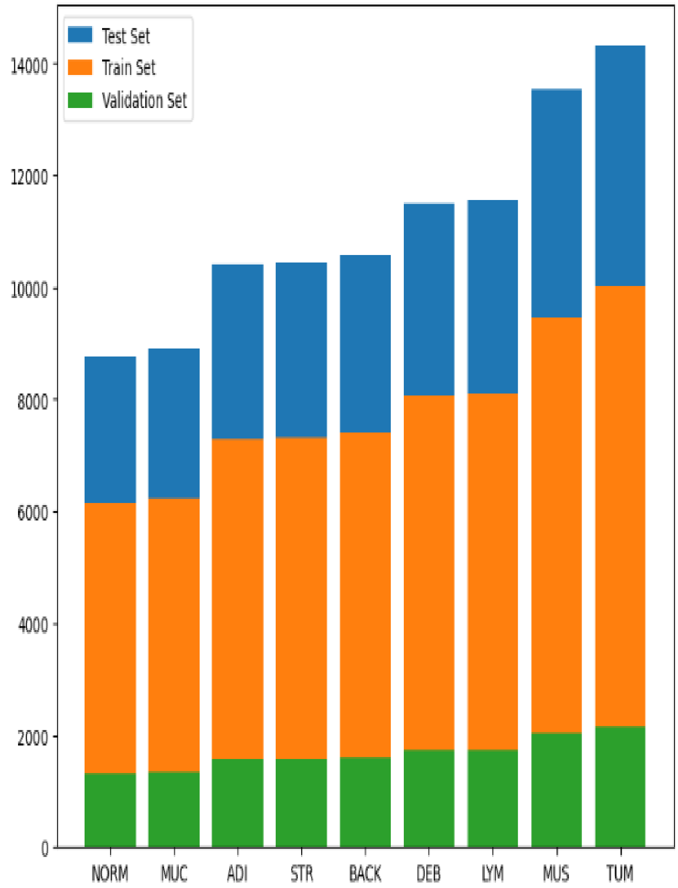

Figure 4: Shows the histogram of dataset for 8 classes

Histogram visualizations for eight classes are shown in Figure 4, which illustrates the dynamics of the distribution of classes in the data set.

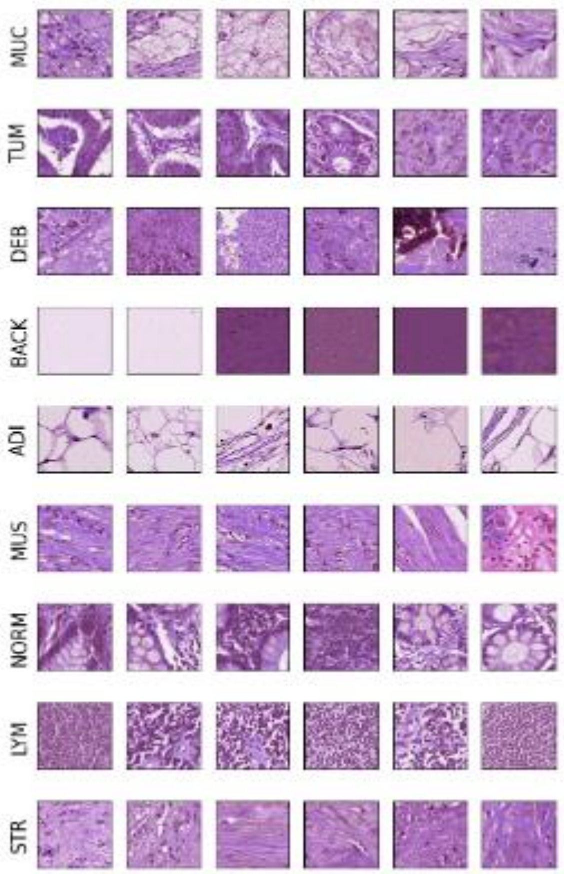

Figure 5: Visualization of data samples of different classes

As presented in Figure 5, all the classes of colon cancer are visualized with corresponding saple histology images.

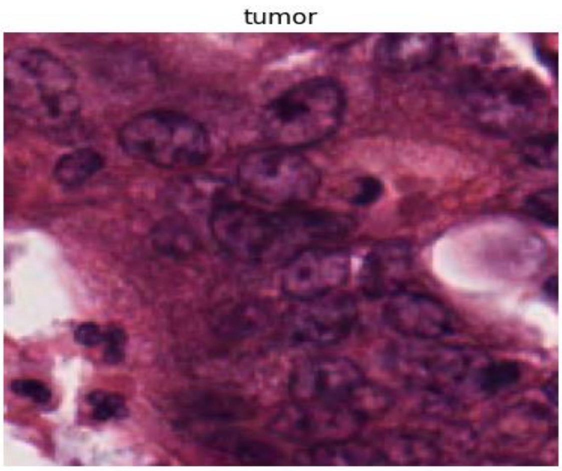

Figure 6: Tumor class is correctly detected as tumor class

As shown in Figure 6, the suggested framework was able to accurately identify the provided histology sample. For example, it matched the ground truth and displayed the prediction result as the tumor class.

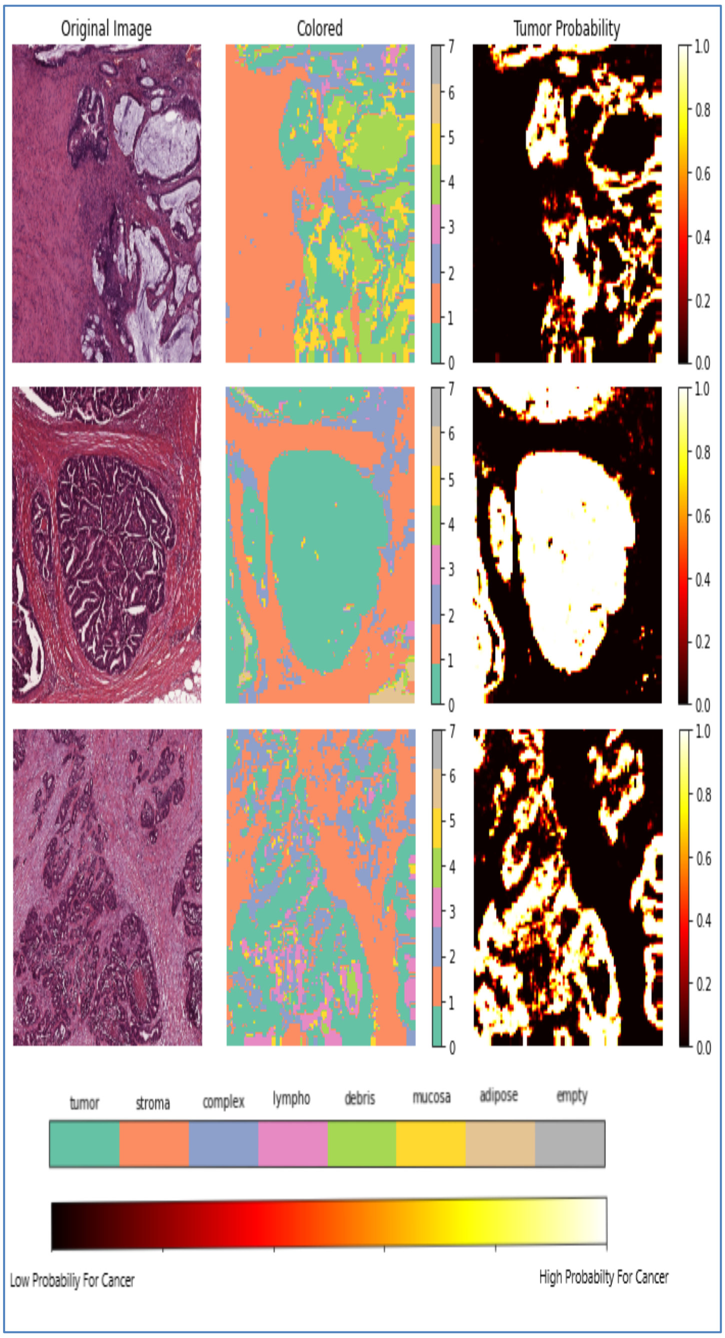

Figure 7: Shows experimental results with test samples and predictions

The suggested framework can identify test samples and classify them into eight different class labels, as shown in Figure 7. This feature is essential for creating the kind of decision support system that hospitals need. Three original samples, their colorful pictures, and tumor probabilities were supplied by the findings. When making decisions on patient engagement and treatment, clinicians may better grasp the seriousness of the issue with the use of this type of visualization.

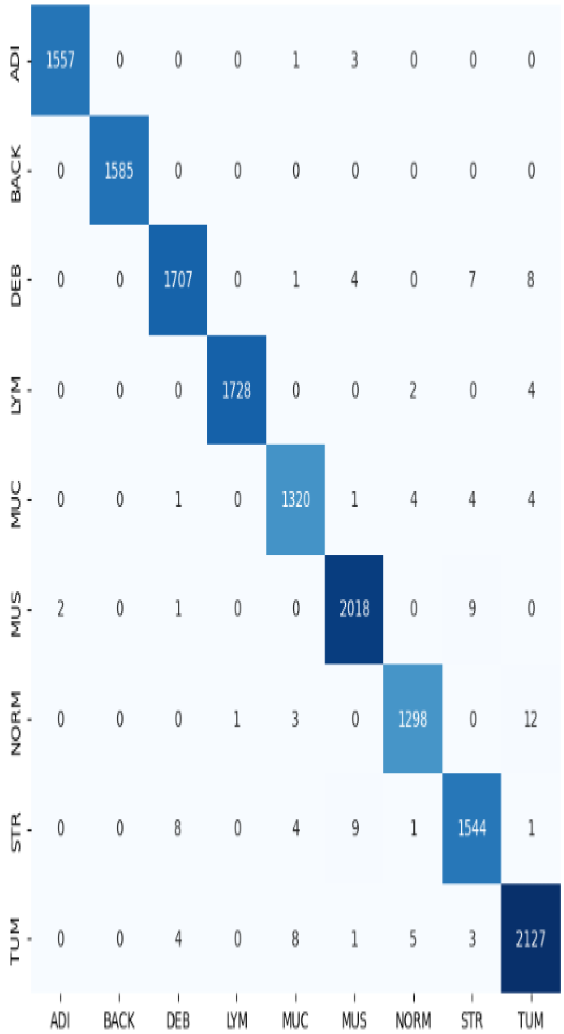

Figure 8: Confusion matrix

The confusion matrix for each class label, as shown in Figure 8, represents the dynamics of colon cancer detection.

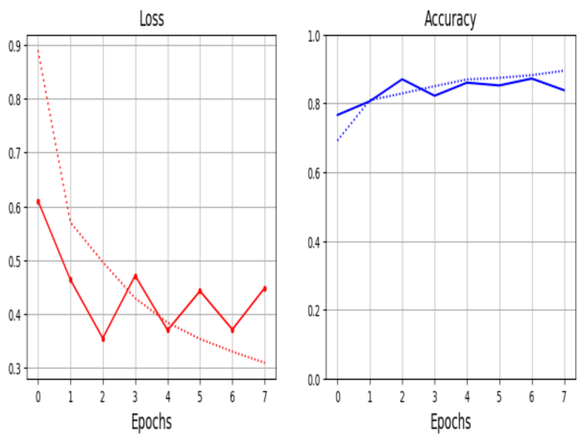

Figure 9: Performnace of enhanced ResNet50 with RMSProp optimizer

Training loss and test loss are plotted against the number of epochs (left) as shown in Figure 9. Additionally, it displays test and training accuracy against the number of epochs (right). Greater precision denotes superior performance, whereas lower loss denotes superior performance. The model's test accuracy is 87.30%, and its train accuracy is 90.68%.

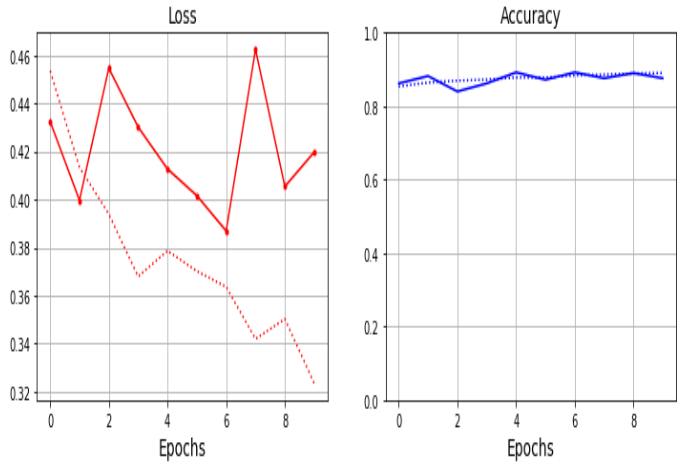

Figure 10: Performnace of enhanced ResNet50 with data augmentation and RMSProp optimizer

Training loss and test loss are plotted against the number of epochs (left) as shown in Figure 10. Additionally, it displays test and training accuracy against the number of epochs (right). Greater precision denotes superior performance, whereas lower loss denotes superior performance. Following data augmentation, the model's train accuracy is 89.03%, while its test accuracy is 87.59%.

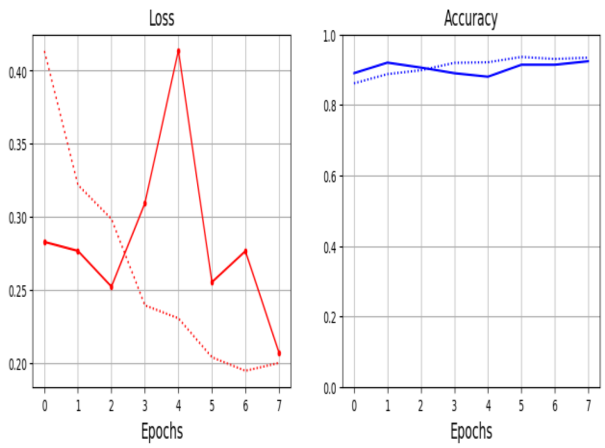

Figure 11: Performance of enhanced ResNet50 with data augmentation after finetuning with SGD optimizer

Figure 11 shows how test loss and training loss vary with the number of epochs (left). Additionally, training accuracy and test accuracy against the number of epochs are displayed (right). Improved performance is shown by lower loss and higher accuracy, respectively. The model has a train accuracy of 93.40% and a test accuracy of 92.40%.

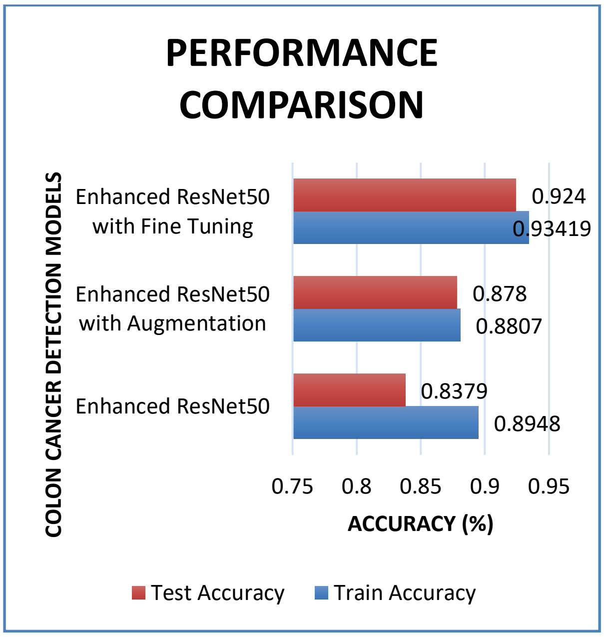

Figure 12: Performance comparison of different ResNet50 variants

Performance of upgraded ResNet50 with transfer learning and its variations is given, as shown in Figure 12. With an observed 89.48% train accuracy and 83.79% test accuracy, the upgraded ResNet50 performs significantly in the detection of colon cancer. Its performance is further boosted when upgraded ResNet50 is employed for cancer diagnosis and data augmentation is applied to training samples. The test's accuracy increased from 83.79% to 87.80%. The exam accuracy has increased by 4.01%, which is really noteworthy. To avoid overfitting and increase accuracy, the improved ResNet50 model is further optimized using the SGD optimizer and fine-tuning the learning rate. The upgraded ResNet50 has performed better after fine-tuning. 94.56% is its train accuracy and 92.40% is its test accuracy. It indicates that the increased ResNet50 's fine tuning resulted in an 8.61% improvement.

6. CONCLUSION AND FUTURE WORK

We introduced a Deep Learning based Colon Cancer Detector (LbCCD) framework in this study. Our architecture is meant to be expandable in the future to accommodate new features. With LbCCD, colon cancer may be automatically diagnosed without needing a doctor's knowledge. It may be included into the Clinical Decision Support System (CDSS) of already-available medical software. Based on empirical research, we concluded that the ResNet50 deep learning model is a good fit for detecting colon cancer. We improved ResNet50 by adding more layers through the use of transfer learning. Our algorithm called Enhanced ResNet for Colon Cancer Detection (ERCCD), makes use of improved ResNet50 to leverage diagnostic accuracy and learn from training samples. In addition, the platform allows for model modification, data augmentation, and fine tuning to increase cancer detection accuracy. Using datasets from colon histology, we conducted an empirical investigation and found that, with improved ResNet50 after finetuning, RRCCD achieved 92.40% accuracy which is better thanother models. We want to enhance our framework in the future by adding other pre-trained models and potential extensions to create a very reliable colon detection system.

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