Classification of Lung and Colon Cancer Using Deep Learning Method

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Abstract. Cancer seems to have a significantly high mortality rate as a result of its aggressiveness, significant propensity for metastasis, and heterogeneity. One of the most common types of cancer that can affect both sexes and occur worldwide is lung and colon cancer. It is early and precise detection of these cancers which can not only improves the rate of survival but also increase the appropriate treatment characteristics. As an alternative to the current cancer detection techniques, a highly accurate and computationally efficient model for the rapid and precise identification of cancers in the lung and colon region is provided. For the training, validation and testing phases of this work, the LC25000 dataset is used. Cyclic learning rate is employed to increase the accuracy and maintain the computational efficiency of the proposed methods. This is both straightforward and effective which facilitates the model to converge faster. Several transfer learning models that have already been trained are also used, and they are compared to the proposed CNN from scratch. It is found that the proposed model provides better accuracy, reducing the impact of inter-class variations between Lung Adenocarcinoma and another class Lung Squamous Cell Carcinoma. Implementing the proposed method increased total accuracy to 97% and demonstrate computing efficiency in compare to other method.

Keywords: Convolutional Neural Network, Transfer Learning, Lung Cancer Pathology.

1 Introduction

The word cancer is used to describe a large group of diseases that affect various body parts. One of the characteristics that distinguishes cancer is the unrestrained, fast proliferation of aberrant cells that cross their normal borders and have the potential to infiltrate other organs. International Agency for Research on Cancer (IARC) of the World Health Organization (WHO) [1] reports that in 2020, cancer is the greatest cause of death worldwide, accounting for 19 million new cases and approximately 10 million deaths. The main reason for death from cancer is metastasis, which occurs when cancer spreads from its primary place to another organ of the body without the aid of adhesion chemicals. Any organ in the human body could get cancer, but the lung, colon, rectum, liver, stomach, and breast are the most frequently affected organs. The most common cancers that cause deaths in both men and women are colon and lung cancer. Globally, there were 2.21 million new cases of lung cancer in 2020, 1.93 million cases of colorectal cancer, 1.80 million lung cancer-related deaths, and approximately 1 million colorectal cancer deaths [2]. Behaviors as a high body mass index, a drinking habit, or smoking are factors in the development of cancer. Along with genetic ones, there are physical toxins like radiation and UV rays in [2]. When lung cells mutate, they grow uncontrollably and combine into a mass known as a tumor, which is when they turn malignant. The colon, the last part of our digestive system, may develop colon cancer if it has malignant cells. In the majority of cases of colon cancer, a tumor develops as normal cells that line the colon or rectum enlarge out of control.

Without a broad spectrum of diagnostic techniques, cancer detection task is difficult. Patients usually have little or no disease symptoms, but by the time they appear, it is frequently too late. Understanding metastases is a critical topic of cancer research because metastatic illness causes

90% of cancer deaths [3]. Colon cancer frequently metastasizes to the liver, lungs, and peritoneum, while lung cancer frequently metastasizes to the brain, liver, bones, and other areas of the lungs. Although symptoms are commonly linked to the presence of cancer cells in the organ where they spread, the metastatic cells would look under a microscope to be sick primary organ cells [4]. Early detection and appropriate treatment are now the main ways to reduce the frequency of cancer-related mortality [5]. If colon cancer is discovered at Stage 0, for instance, more than 92 percent of patients between the ages of 18 and 73 can live with the appropriate medication, and 83% in Stage 1, 67%, in Stage 2, 11% in Stage 3. The relative lung cancer survival rates are 69%, 50%, 29%, and 8% in [6]. The high cost of screening equipment prevents many people from using them. 70% of deaths caused by cancer in countries other than those with greater incomes [2]. The solution to this issue may lie in a field that has nothing to do with medicine. It is medical field which use deep learning for numerous purposes in [7].
In order to categorize and forecast different kinds of biological signals, machine learning methods have been utilized. Deep Learning (DL) techniques have been developed, allowing machinery that deals with data which are by nature high in dimension including images, videos. A CNN model was developed from scratch to extract features from pathological images, carry out end-to-end training, gradually and accurately categorize the Lung and Colon Cancer pathological images. The hyperparameters were tuned to ensure the best configuration and a learning process cyclical in nature was used to reduce computation and make the model faster.

The following is a list of this paper's key contributions:

1. In order to improve classification performance, a scratch CNN model is developed.
2. The inclusion of the cyclical learning rate approach in the proposed model delivers substantial performance increases and lowers the computational expense.
3. To increase the accuracy and compare accuracy with different transfer learning methods from others method.

2 Related Works

For more than 40 years, researchers have studied the automatic assistant diagnosis of cancer by classifying histopathological images into non-cancerous or malignant patterns for analysis, which is the initial aim of the image analysis system. The complexity of image analysis, however, made it difficult to deal with the complexity of histological images. Approximately 40 years ago [8], investigated the possibility of automatic image processing, but the difficulty of analyzing complex images makes it still difficult today. Back then, implementing machine learning-based computer-aided diagnosis (CAD) required feature extraction as a crucial step. Different cancer ontologies have been looked into in studies by in [9] provide a thorough overview of cancer diagnosis by carrying out tests of various deep learning methods. Additionally, it offers comparisons of the various prominent architectures. The next few paragraphs, briefly discuss the previous works by the researcher.
A representational Sparse in nature Classification (mSRC) technique of diagnosing cancer of lung was described by in [10]. The authors used samples from needle biopsies to automatically segment regions of nuclei numbered 4372 of the diagnosis of cancer in lung. This approach has average classification accuracy of 88.10%. In [11], on the basis of the examination of CT scan images, to classify cancer an approach was followed by authors and which was dealing with CAD. They took six different statistical feature and forward and its reverse propagation are the two types of networks which were used. The comprehensive analysis demonstrates that skewness, when combined with ANN with back-propagation, yields the best classification results. In [12], a classification method which is free of label for grading cancer in colon was published. Different dedifferentiation states of colon cancer and infrared spectral histopathology imaging were used in this work. Random Forest, a supervised learning technique based on Decision Trees (DT), carried out the classification (RF). In [13], a technique was proposed which can analyze colonoscopy video to identify cancer and that can automatically identify polyps from colonoscopy video was described by Yuan et al. They employed AlexNet, a well-known CNN based architecture, for classification, which had an accuracy rate of 91.47%. In [14], a technique for cancer in lung, stage detection was proposed by Masood et

al. The researchers evaluated their model using six different datasets and used CNN and DFCNet in their research. A swarm optimization- based technique for cancer in lung prediction was presented in [15] using images from various sources. A maximum accuracy of 98% was attained using their learning algorithm of choice, the Recurrent Neural Network (RNN).
In order to detect colorectal cancer from colonoscopy videos, A method which is based on neural network was and weights of binary nature was used to classify in [16]. Collected data was evaluated and achieved classification accuracy of more than 90%. In [17] an approach of automatic in nature was developed for detecting lung cancer. They used the Wolf heuristic feature selection approach and bin smoothing for the normalization mechanism. The classifier applied in this study neural network of learning of ensemble kinds was the most intriguing aspect of the study's methodology. Its accuracy was over 99%.
In [18], proposed a CNN model after extracting more than three sets of features, from histopathological images of lung and colon cancer. Authors used convolutional layers of numbered three pooling double times, single batch normalization with dropout for this classification task. Authors have also showed a comparison of related research where the proposed method of 96.33% accuracy the method can identify tissues of desired nature, performing well than other works.
As a result, it can be concluded that the classification of both lung and colon cancer has had a significant impact for a long time. Deep learning models combined with a wide range of configurations have recently exceeded current state-of-the-art methods, as well. There is a huge amount of scope for initiating innovation and development in this developing research field to overcome this.

3 Datasets

3.1 LC25000

This dataset, has images total of 25000 and which are of different types - total five in number [19]. These variations include lung adenocarcinoma, lung squamous cell cancer, benign lung tissue, benign colonic tissue, and lung adenocarcinoma. The authors principally gathered 1250 images of tissues which are of cancer types (250 images of each category). Several techniques were used to increase images of each class (5000 images in each class). Before using the augmentation techniques, to make a square of 768X768 pixels from their original size of 1024X768 cropping was used. The dataset has the nature of compliance, and validation, and use of every image in the dataset is totally free. The dataset's contents are listed in Table 1, along with the class names.

Table 1: LC25000 Dataset Summary

Cancer Type	**Samples**
Colon Adenocarcinoma	5000
Colon Benign Tissue	5000
Lung Adenocarcinoma	5000
Lung Benign Tissue	5000
Lung Squamous Cell Carcinoma	5000
Total	**25000**

4 Methods

4.1 Cyclic learning Rate

CNNs are one of the most effective architectural designs for the issue of image classification. To extract the most unique features from an image's pixels, CNNs utilize filtering methods. The most essential hyperparameter to adjust while deep learning deep neural networks is the learning rate, that is well known.
The learning rate can cycle between acceptable boundary values using this strategy rather than monotonically decreasing. Training using learning rates of cyclical in nature rather than choosing

values increases accuracy without the necessity of trial and error method and also frequently requires fewer iterations.
The fundamental idea behind cyclical method is based on the idea that speeding up learning could have both short-term detrimental effects and long-term beneficial outcomes. This discovery inspires the concept that rather of using a stepwise fixed or exponentially declining value, the learning rate should be allowed to vary within a range of values. Due to the fact that the triangle window is the most straightforward function that contains both linear rising and linear decreasing, this led to its adoption which is illustrated in Figure 1.

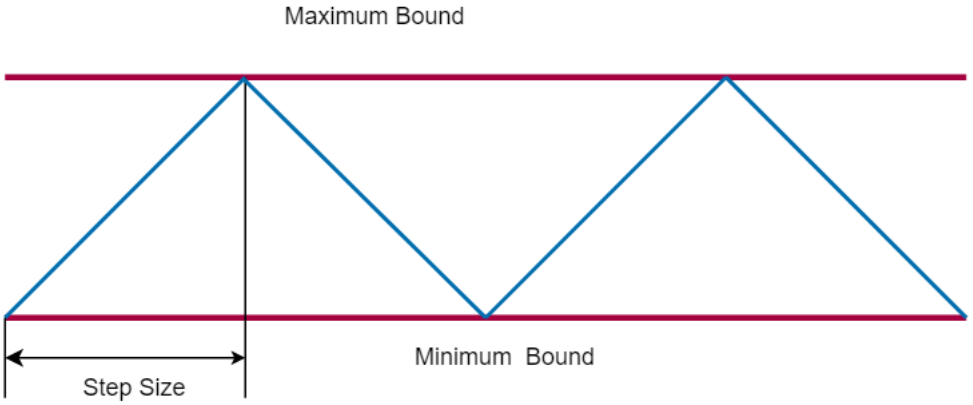

Fig. 1: Triangular Learning Rate Policy

The loss was estimated against the learning rate, and based on the learning rate in Figure 2, the base lr value was adjusted to 0.003 as the loss was declining.

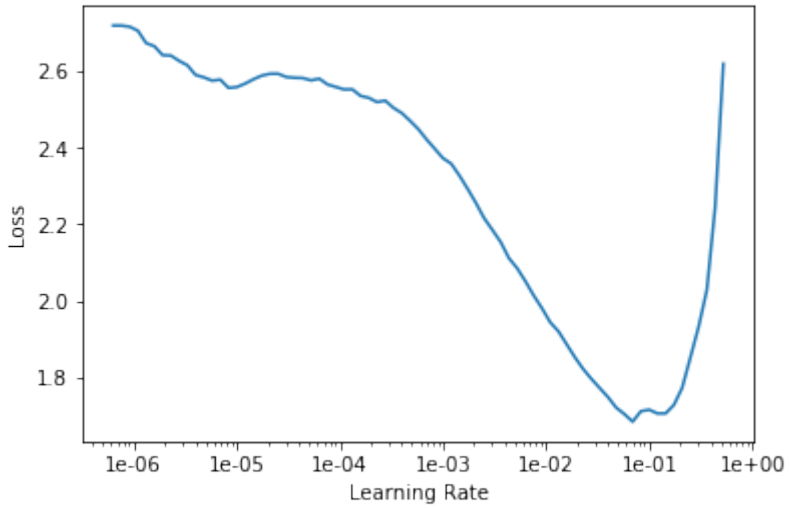

Fig. 2: Loss versus Learning Rate (base learning rate)

The best learning rate is determined after 8 training epochs by re-running the cyclic learning rate. The distinction of the learning rate at the onset of loss diminution and at the juncture where the

loss's declination transforms into irregularity or commences to escalate constitutes optimal limits for specifying the base and maximum learning rate, respectively[20]. In conformity with this, the base learning rate is instituted at the former value, and the maximum learning rate is established at the latter value, as exemplified in Figure 3, where the base lr was set to 0.0045 and max lr was set to 0.0301.

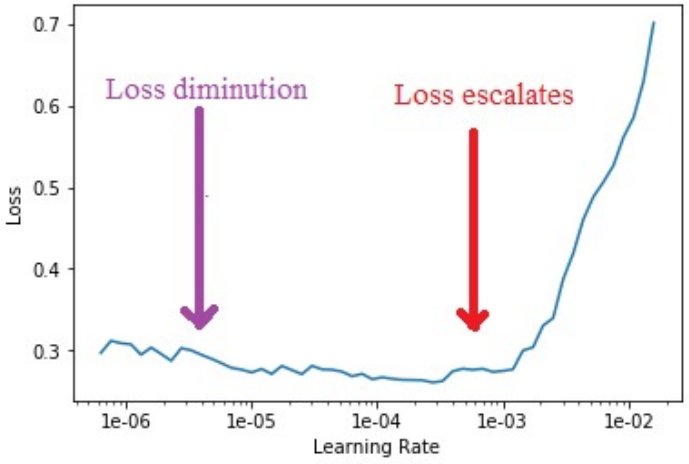

Fig. 3: Loss versus Learning Rate

4.2 Proposed CNN Architecture

In a 3D space with two spatial dimensions (width and height) and one channel dimension, a convolution layer attempts to learn filters. RGB images with a size of 64x64 pixels were used when using this layer. Thus, mapping cross channel correlations and spatial correlations are both accomplished using a single convolution kernel. The input data is divided into three or four smaller areas than the original input space, and any cross channel correlations are then mapped in these smaller 3D spaces using standard 3x3 or 5x5 convolutions. In deep learning frameworks a depth wise separable convolution commonly referred to as a "separable convolution"—consists of a depth wise convolution. A pointwise convolution followed by a spatial convolution carried out individually across each input channel. Despite to separable convolution might implies, this is not to be mistaken with a spatially separable convolution. Although a ReLU non-linearity follows both operations, depths wise separable convolutions are typically performed without nonlinearities.
Each layer of the network can learn more independently due to the layer of batch normalization. It uses normalization to adjust the output of the prior layers. The input layer is scaled during normalization. When batch normalization is used, learning is more successful. To avoid overfitting the model, batch normalization was employed as a regularizer. Three Residual blocks were used in the model. Spatial convolution layers and batch normalization make up the residual block.
Dropouts are a regularization technique that prevents model overfitting. Neurons in the network are modified in some percentage randomly as dropouts are added. When neurons are turned off, the connections to their incoming and outgoing neurons are also disconnected. A pooling method called global average pooling is intended to take the place of fully connected layers in conventional CNNs. One feature map should be produced for each associated classification task category. After creation of the model, the softmax activation function was used to classify the lung and colon histopathology images.
The convolutional layer, batch normalization layer, and residual block were just a few of the layers that constitute a CNN's architecture, as depicted in Figure 4.

Our proposed model's properties are described in Table 2.

Table 2: Property Specification Table of Proposed Model

Specification	Value
Input image	64x64x3
Activation of Conv_2D layers	Relu
Pooling 2D layers	3x3
Output layer activation	Softmax
Optimizer for compilation	Adam

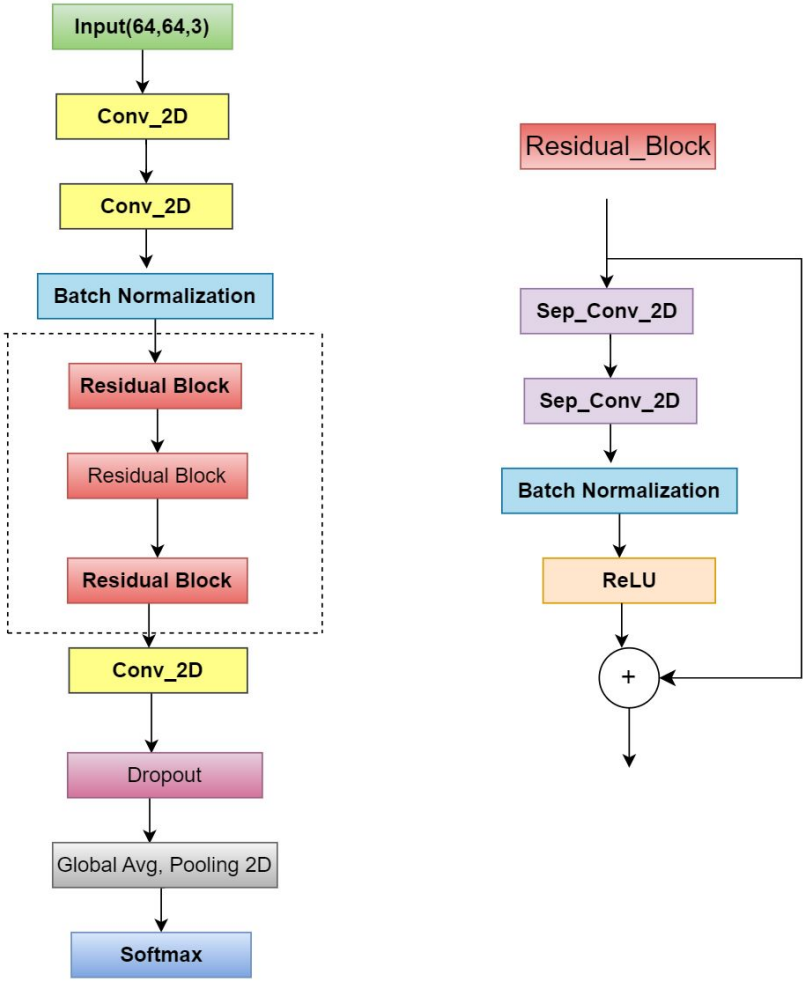

Fig. 4: Proposed Convolutional Neural Network Architecture

5 Result Analysis

In this part, the system configurations have been outlined. The best model's f1-score, recall, and precision are a few of the accuracy metrics that stand out. For further study of the best model, the classification report, confusion matrix, and performance graphs are evaluated.

On LC25000, multiclass classification analyses are performed. The down sampling technique was employed to reduce the size of the image to 64x64. In the LC25000 dataset, various pre-trained transfer learning models were also used. The following are the accuracy comparisons between several transfer learning models and ours:

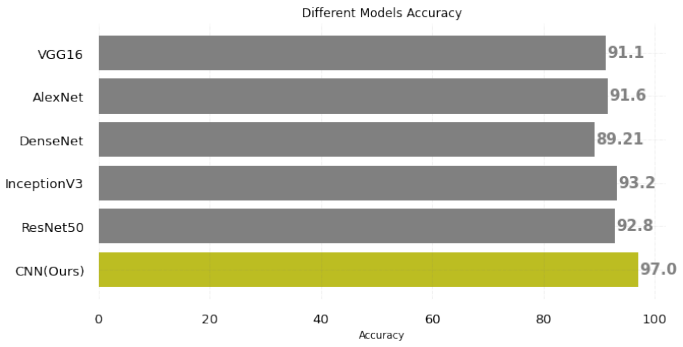

Fig. 5: Accuracy Comparison of Different Models

It is clear from Figure 5 that proposed model's testing accuracy outperforms transfer learning models including those used by other authors. The nature of benchmark datasets and histopathology slides are very different, therefore features at low levels retrieved using transfer learning methods that rely on benchmark datasets are not very relevant in this instance.
An optimizer is a method, such as a function or algorithm, that modifies a neural network's characteristics. It helps to increase accuracy and decrease overall loss. The following three optimizers were utilized in this model: Adam, SGD, and RMSProp are shown in Figure 6.

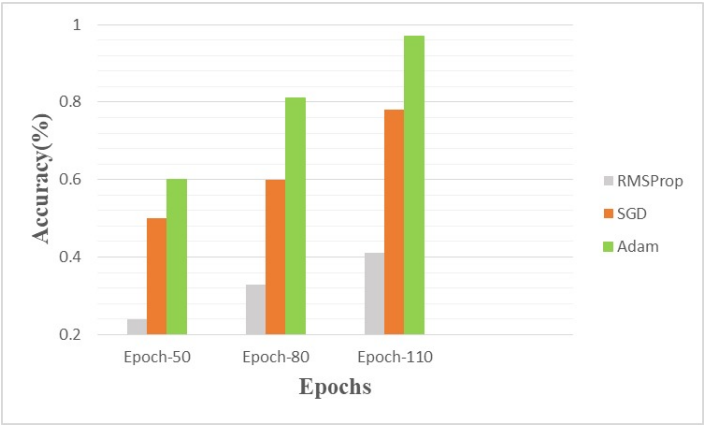

Fig. 6: Optimizer Comparison Curve

Adam's accuracy in the model was the highest according to the following figure and for this Adam was chosen because its accuracy in the model was the highest, as shown by Figure 6.
The samples numbers that are before processing the model hyper tune is the size of each batch. The batch size utilized was shown in Figure 7, and it was determined by the number of samples before processing the model hyperparameter tune.

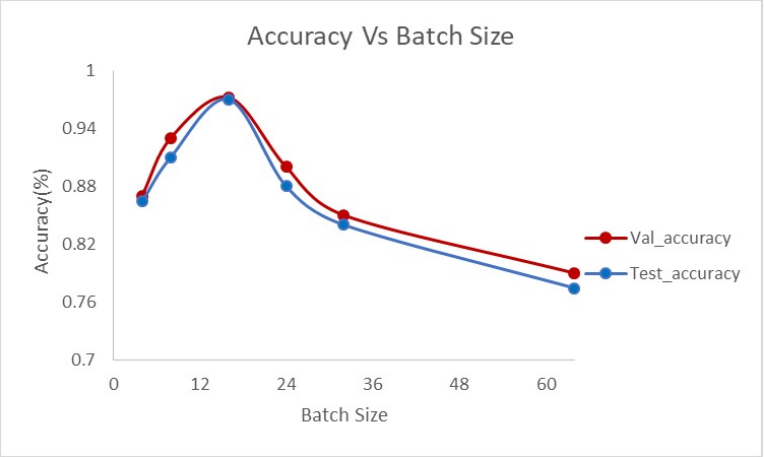

Fig. 7: Accuracy versus Batch Size

Batch size 16 was chosen because it provided the highest accuracy among others, as determined by the comparison curve.

Table 3 explains how the proposed model's hyperparameters were configured.

Table 3: Hyperparameter Configuration of Proposed Model

Hyper Parameter	**Range**	**Optimal Value**
Batch Size	4,8,16,24,32,64	**16**
Epoch	50, 60,80,90,100,110	**100**
Optimizer	Adam, RMSProp, SGD	**Adam**
Dropout	0.20,0.30.0.4,0.50	**0.4**

5.1 Proposed Model Output

A ratio of 80:10:10 for training, validation, and testing is maintained when the dataset is split in the proposed model. Several parameters are taken into account for performance analysis, as depicted in Figures 8 and 9, to demonstrate the performance of the proposed approach. The accuracy of training and validation was included in Figure 10.

	precision	recall	f1-score	support
0	1.00	0.91	0.96	500
1	0.97	1.00	0.98	500
2	0.93	0.94	0.94	500
3	1.00	1.00	1.00	500
4	0.94	0.97	0.96	500
accuracy			0.97	2500
macro avg	0.97	0.97	0.97	2500
weighted avg	0.97	0.97	0.97	2500

Fig. 8: LC2500 Dataset Classification Report

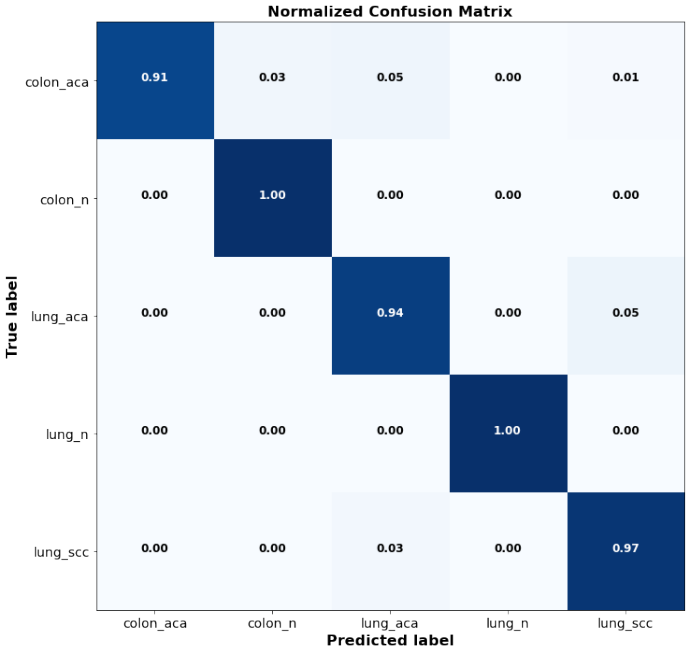

Fig. 9: LC25000 Dataset Normalized Confusion Matrix

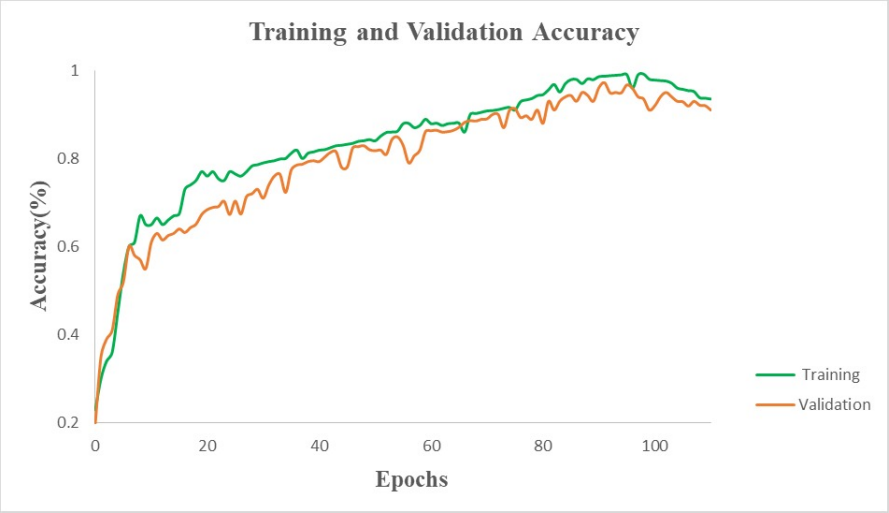

Fig. 10: Training and Validation Accuracy Curve

The experiment's results for multiclass classification accuracy were measured and compared to those of other authors, as shown in Table 4. Though the same dataset was not used by all of the authors, as the purpose of the task remains the same, they were compared with the proposed approach. The classification accuracy was 97% and it significantly reduces inter-class variation between two forms of cancer in Lung Adenocarcinoma and Squamous Cell Carcinoma. In prior studies [21], [22] the authors neglected to integrate residual blocks, which are essential components that enable the establishment of deeper network architecture and effectively alleviate the vanishing gradient problem. Additionally, the implementation of skip connections within Residual Networks facilitates the seamless transmission of information across the network, thereby facilitating optimization. The

CNN models in references [22] and [23] suffer from limited feature extraction and overfitting issues due to their shallow network architecture. The proposed model incorporates three ResNet blocks and the use of separable convolution layers within these blocks, which significantly reduces the number of parameters required and results in a compact model with expedited training times. This proposed model reduces 1.95 times training times than described in [24].

Table 4: Author Accuracy Comparison Table

Author	Types of Images	Model	Accuracy	Precision	Recall	F Measure
Y. Shi et al.,[25],13	Biopsy Image	mSRC	88.1	84.6	91.3	86.6
Y. Xu et.al, [26],13	Histopathological	SVMs		73.7	68.2	70.8
Kuruvilla et al.,[27] ,14	CT scan	ANN	93.3		91.4	
Sirinukunwattana K et.al, [28], 16	Histopathological	CNN		78.3	82.7	80.2
Kuepper et.al, [23], 16	Histopathological	RF	95		94	
W. Shen et.al, [24], 17	CT scan	CNN	87.14		93	
Z.Yuan et.al, [13], 17	Colonoscopy	AlexNet	87.14		91.76	
T.Babu et al.,[29],18	Histopathological	RF	85.3			85.2
M.Akbari et al.,[30],18	Colonoscopy	CNN	90.28	74.34	68.32	71.2
Suresh et.al, [21], 20	CT scan	CNN	93.9		93.4	
M.Masud et.al, [22], 21	Histopathological	CNN	96.33	96.39	96.37	96.38
Proposed	**Histopathological**	**CNN**	**97**	**97**	**97**	**97**

It can be concluded from Table 4 that the accuracy of the proposed method surpasses that of other authors.

6 Conclusion

Lung and colon cancer are attributed as mostly caused cancer types among all other types. Early identification of cancer can help patients rate of survival to increase. The prime purpose of the proposed method was to provide a more robust and reliable approach for these two forms of cancer. For this detection, transfer learning was used on a dataset of 25,000 histopathological images of colon and lung tissues. When using the suggested scratch CNN method, accuracy was greatly improved and reached 97%. The proposed methodology offers improved accuracy over current methods for detecting lung and colon cancer while also taking less time and using less computational resources. All the experiments verify the effectiveness of the proposed method regarding the task of detecting cancer. Future incorporation of attention with scratch CNN model to increase the classification accuracy and explore more details of the image.

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