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DEEP INVOLUTION NETWORK COUPLED WITH RETINEX ALGORITHM FOR LUNG AND COLON CANCER DETECTION

Mumtaz Ali[1], Abdul Qadeer[2], Hitesh Kumar[3], Sayed Ahmed Ali Shah[4], Khalid Hussain[5]

[1,2,3,4,5]Department of Computer Systems Engineering, Sukkur IBA University, Pakistan.

[*]Corresponding author: (**mumtaz.ali@iba-suk.edu.pk**)

Article Info

Abstract

In recent times cancer has drastically increased as one of the leading diseases that has higher mortality rates. Among the malignant cases, lung and colon cancer types rank at the top of the list of cancer-related fatalities around the globe. Most of the malignant cases may be managed, if the histological diagnosis has been done at the earliest stages. The diagnosis conventionally relies on human experts; however, deep learning methods have emerged as a contemporary alternative to such experts. There are a number of studies which report such deep learning models. Despite their significant contribution, they still lack deployable accuracy. In this study, a deep learning model based on Deep Involution Neural Networks has been proposed to classify lung and colon cancer cases. Along with a deep learning model, a preprocessing method that incorporates a multi-scale Retinex algorithm has been used to improve the appearance of histopathological images. The proposed model achieves state-of-the-art results on lung and colon cancers.

Keywords:
Lung and Cancer, Deep Involution Network, Retinex Algorithm.

1 Introduction

Recently, cancer has been considered a leading cause of the total mortality globally [1]. Among the cancer-related fatalities, lung and colon cancer are a major cause. Lung cancer, if not controlled properly, 19% of the patients not survive even five years after the onset of the disease [2]. Global statistics such as GLOBOCAN 2018, report that over two million cases emerge every year, and nearly 1.8 million people die within a year [3]. The World Health Organization (WHO) also reports very similar statistics. According to WHO for non-communicable diseases, every year 71% of deaths globally are caused by cancer [4]. Apart from the rapid progression of the disease, lack of health care facilities, particularly in underdeveloped regions of the world, makes the disease control a challenge [5]. In the year 2022, GLOBOCAN reported that 2 million premature deaths which make up 18% of the total deaths around the world are caused by liver, colorectal, breast, and Lung tissue cancers [6].

Among the other types of cancers, lung cancer also shows higher rates of fatalities. Mainly, there are a couple of categories of lung malignancies, abbreviated as SCLC and NSCLC, which refer to small-cell-lung-cancer and non-small-cell-lung cancer. Due to its neuroendocrine properties, SCLC is classified as a cancer that rapidly progresses once the onset of the symptoms are evident in a patient. SCLC alone is responsible for nearly 15% of lung cancers. On the other hand NSCLC is responsible for 85% cases of lung cancers. The NSCLC includes squamous, large cell carcinoma and adenocarcinoma [7]. Similar to lung cancer, colon cancer is one of the fatal diseases. Biggest concern is that lung and colon cancers can occur concurrently, making the treatment options very difficult. Colon cancer and rectal cancer types are jointly called as colorectal cancer. It is mostly adenocarcinoma which accounts for nearly 96% of colorectal cancer types. Similarly, carcinogenesis is cancer that progresses in multiple stages. Initially, it mutates to alter the DNA. Due to that reason it progresses at an insanely rapid rate. The growth of the cells becomes almost uncontrollable; hence, tumors are clearly noticeable in such patients even at early stages [8].

A number of factors contribute to the progress of carcinogenesis, tobacco, obesity, alcohol consumption, genetic tendencies and radiation are among the major causes. As the disease progresses, at the beginning, some of the symptoms are very evident, for instance, cough, bruising, weight loss, muscle aches, fatigue, vomiting etc. [8]. Although, most of the symptoms are very common, they can vary from patient to patient. Diagnosis of the disease at the beginning plays a vital role for the survival of the patients. Despite the clarity of symptoms, early-stage diagnosis is very challenging, especially if the disease is combined with a conventional flu or fever like annoyance. Other than these challenges, the underdeveloped countries

have access to only 26% of pathology services. Developed countries may have more than 90% of pathology services available, however, despite this high level of diagnostic facilities, cancer cases are among the most lethal causes of death. In recent times, the introduction of computer aided diagnostic (CAD) methods have brought a new hope [9]. The CAD techniques contribute significantly to boost the histopathological diagnosis. Other than conventional approaches, machine learning methods are very popular due to highest rates of precision and accuracy.

Table 1: Overview of the cases and fatalities

Cancer Type	Cases	Cancer Type	Fatalities
Breast	2261419	Breast	684996
Cervix uteri	604127	Pancreas	466003
Colorectum	1931590	Colorectum	935173
Liver	905677	Liver	830180
Lung	2206771	Lung	1796144
Esophagus	604100	Esophagus	544076
Other Cancers	8275743	Other Cancers	3557464
Prostate	1414259	Prostate	375304
Stomach	1089103	Stomach	768793

The extent of spread of tumors drastically affects the nature of the tumors [11]. Conventionally the tumors in different patients have different shapes and heterogeneous behavior; therefore, CAD systems face significant challenges in analyzing the texture of the tumors and ultimately identifying the type of cancer [16]. In recent years, image analysis based on homology has acquired huge attention [12]. For instance, the authors in [13,14] successfully applied different segmentation techniques to detect lung and colon cancers. Taking such studies as inspiration, this study is presenting a deep learning model based on Deep Involution Neural Networks to classify and diagnose the lung and colon malignancies. This study has the following contributions.

- The method proposed in the study incorporated a novel architecture based deep involution neural networks for the classification of lung and colon malignancies.
- It used an effective preprocessing technique based Multi-scale Retinex Algorithm
- The proposed model achieves state-of-the-art results for the classification of lung and colon malignancies.

2 Related Work

Critically observing the previous works, it is evident that machine learning models have been able to learn features and get trained on large datasets. Especially, they have shown a great deal of potential for medical image analysis. One need only look at the results to see that these algorithms have been more than capable in their performance across an array of disciplines, from pattern recognition to healthcare automation [15]. In cancer detection, for example, deep learning and machine learning are ubiquitous. CNNs, being a

subtype of machine learning, have made short work of classifying cancers in skin, lung, colon, and breast when applied to histopathological images [16].

There is no shortage of examples in the literature. Joshua et al. have put forward a deep learning method for the classification of colon cancer [17]. In another case, the authors put together a Spatially Constrained CNN on 20,000 images to sort four kinds of nuclei in colon cancer; by sidestepping the need for segmentation they were able to come up with an F1-score of 80.2% [18].

Yuan and colleagues have taken deep learning a step further with an AlexNet model for the automatic spotting of tumors in colonoscopy video. From 3463 frames of live footage they were able to reach 91.47% accuracy [19]. Akbari et al. came in at over 90% with a binarized weighting technique for colorectal cancer, working off the ASU Mayo Clinic data [20]. Then there is Toraman et al., who paired SVM and ANN with waveform statistics in an FTIR spectroscopy study for colon cancer diagnosis and saw a 95.71% hit rate [21].

Lung cancer has also been well served by these methods. Satvik and Somya Garg turned to pre-trained VGG16, InceptionV3 and ResNet50 architectures on histopathology images and, after some image augmentation to boost the model, posted accuracy figures between 96 and 100 percent [22]. Nishio was even more precise, using homology-based analysis and Betti coefficients on 15,000 images to classify multi-category lung cancer with 99.3% accuracy [23]. And Hatuwal, working with the LC25000 set, designed a CNN that gave him solid training and validation numbers [24].

The robustness of CNNs in the realm of cancer classification was put on display by Bukhari et al. with their work on ResNet50 for histopathological image classification, a model that proved to have the best sensitivity of its kind [25]. In a related study, Mangal et al. utilized a shallow neural network architecture to distinguish adenocarcinomas from squamous cell carcinomas in lung and colon specimens, reporting high classification accuracy [26].

When it comes to differentiating lung cancer subtypes, Min Li's application of SVM classification alongside Relief feature selection yielded 83.91% accuracy [27]. Adu took a different track by presenting twin networks that hit an accuracy rate of 99.23% [39]. Naresh et al. combined pre-trained CNNs with hand-crafted feature extraction in a DenseNet-121 and Random Forest setup to get good metrics from histopathology images of these cancers [28].

Sethy et al. reported an AUC of 99% and 99.3% accuracy in their classification of lung histopathology via AlexNet, SVMs and wavelet transforms [29]. Then there is Grace et al., who made use of the TCIA dataset to put forward XlmNet, an Extreme Learning Machine system for lung cancer nodule classification that performs well on various metrics [30]. Sandeep et al. have shown that a VGG19 with some improved augmentation can outdo existing techniques in accuracy when classifying lung cancer tissue images [31].

Shanmugam et al. employed optimization approaches like Grey Wolf Optimization with a Decision Tree Classifier to arrive at some very interesting results in their image classification work [32]. And using the LC25000 dataset, Singh et al. put together an ensemble of some machine learning algorithms such as SVM, Random Forest and Logistic regression; they came away with 99.00% across the board accuracy for the detection of cancers on tissues of lung and colon [33]. The strategy was validated on

histopathological images, with the authors making use of regularization and an array of pre-trained CNNs to keep overfitting to a minimum.

3 Methodology

The proposed model is based on deep involution neural network. The architecture of the proposed network has four inner layers. Along with the deep involution model, the method has a preprocessing step that is based on multi-scale Retinex algorithm. The dataset used in this study has histology images; therefore, the images are preprocessed prior to using them for training. The preprocessing mainly improves contrast, color and brightness of the images to improve the appearance. When the images are preprocessed, they are then used for training. With improved appearance of the images, the deep involution network can learn the key features in a better way.

The proposed deep involution network is capable of extracting features in a robust way. The extracted features significantly help to identify the distinct patterns in each class. Hence, the overall workflow of the method, from preprocessing to the network training, is connected in a comprehensive way to classify histology images. Even the heterogeneous texture of the tumors in the images is not hidden from the model. Therefore, it can be confidently observed that the proposed model has the capability to become a useful tool for the diagnosis of the malignant cases of lung and colon cancers simultaneously.

3.1 Deep involution network

A Deep Involution Network utilizes involution, an alternative to traditional convolution, to capture long range dependencies and adapt to spatial variations more effectively. While standard convolution filters are spatial-agnostic (the same weights are applied everywhere) and channel-specific (different weights for different channels), involution is the opposite: it is spatial specific (weights change at every pixel location) and channel agnostic (weights are shared across channels).

A four-layer deep involution network processes an image or feature map through four sequential involution stages:

- Layer 1: Low-Level Feature Extraction The network generates spatial-specific kernels directly from the input image. Because the kernels are customized for every pixel location, this layer quickly captures distinct, fine-grained details like precise edges and local textures across wide spatial areas without needing a massive parameter footprint.
- Layer 2: Mid-Level Structure Aggregation As the features progress to the second layer, the involution kernels adaptively adjust based on the emerging patterns. This layer begins to group local edges into mid-level structures (such as boundaries and simple geometric shapes) by dynamically shifting kernel weights to focus on relevant context.
- Layer 3: High-Level Semantics & Global Context The third layer utilizes larger spatial spans. Because involution scales efficiently over wider receptive fields, this layer integrates broader context across the image. It links separate mid-level structures together, allowing the network to

understand the relationships between different objects or regions in the frame.

- Layer 4: Complex Representation & Task-Specific Output The final involution layer aggregates the rich, globally aware spatial features into highly abstract representations. These refined feature maps capture the complete scene layout and semantic meaning, making them ready for the final task, such as classification, object detection, or dense pixel prediction.

3.2 Multi-Scale Retinex (MSR) algorithm

Among several image enhancement techniques, Multi-Scale Retinex (MSR) algorithm is one of the leading advanced techniques. It takes inspiration from the human visual system. This algorithm tries to replicate how the human visual system perceives color and detail under varying lighting conditions. The MSR is the enhanced version of a previous similar algorithm called Single-Scale Retinex (SSR).

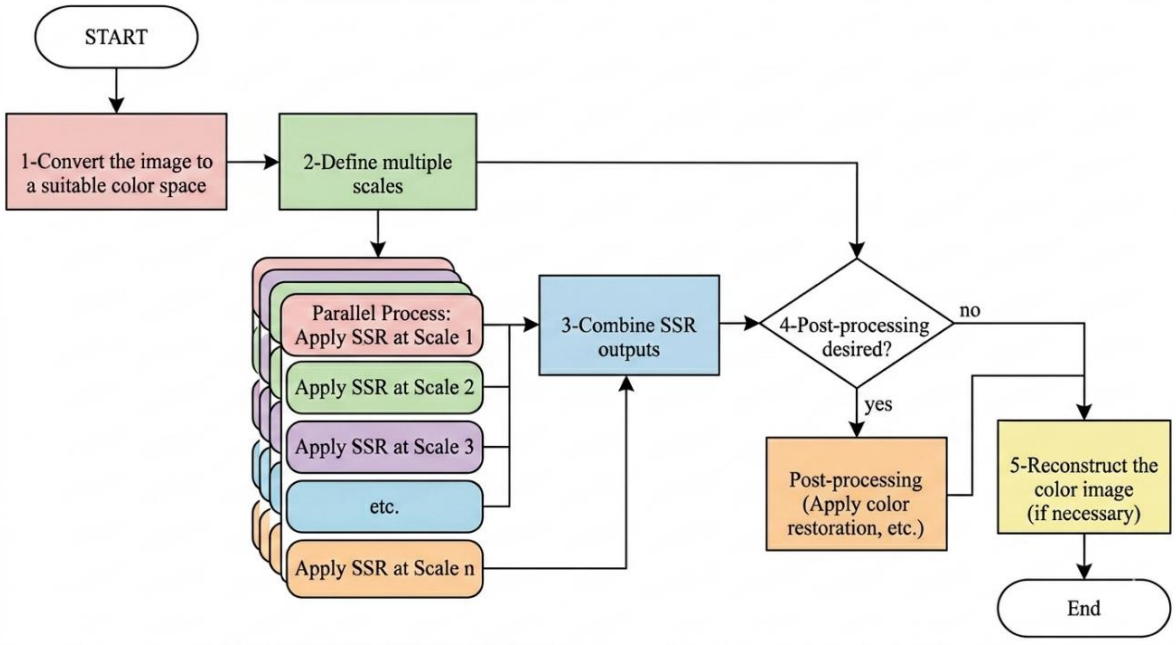

Figure 2: Workflow and steps of MSR

Here is a short breakdown of how it processes an image based on the workflow:

- Color Space Conversion: Initially, the acquired image is converted to a suitable color space (such as logarithmic or isolating intensity channels) to separate luminance from color information effectively.
- Defining Multiple Scales: Instead of using a single surround function (Gaussian blur), MSR defines multiple scales (typically small, medium, and large Gaussian filters).
    - Small scales capture fine details and sharp edges.
    - Large scales preserve overall tonal balance and dynamic range.
- Applying SSR at Each Scale: The Single-Scale Retinex calculation—which computes the difference between the log-transformed original image and the log-transformed blurred image—is

applied independently for each scale.

- Combining Outputs: The outputs from all the individual scales are weighted and combined (usually averaged) to form a single, balanced image that simultaneously achieves dynamic range compression and detail enhancement.
- Post-processing & Color Reconstruction: Optional post-processing (like color restoration to prevent graying-out effects) is applied, and the final image is reconstructed back into the original color space (e.g., RGB) for display.

3.3 LC25000 dataset

This study makes use of the dataset named LC25000. The dataset has samples of histology images for the lung and colon cancer types [34]. There are 25,000 samples based on five different classes. The classes consist of lung and colon tissue samples. The samples in LC25000 dataset are already augmented conventionally using horizontal and vertical flipping. Table 2 shows detailed overview of the dataset. Each class has 5000 samples. The dataset has been distributed for training, validation and testing. Training samples contain 80% of the total samples.

Table 2: Detail of the class IDs and number of samples for Colon_Adenocarcinoma, Colon_Benign_Tissue, Lung_Adenocarcinoma, Lung_Benign_Tissue, Lung_Squamous_Cell_Carcinoma

Name of the class	**ID of the class**	**Sample count**
Aca_Colon	0	5k
N_Colon	1	5k
Aca_Lung	2	5k
N_Lung	3	5k
Scc_Lung	4	5k

3.4 Loss function

For the training of a deep learning network, loss function plays a vital role. Therefore, in this study we use a loss function named label-smoothing loss. This loss function is effective for multiclass classification. The Following equation shows the loss function.

$$L = -(1-\beta)\Sigma[z_j \log(q_j)] - \beta\,\Sigma[z_j \log(1/N)] \quad (13)$$

Here:

β = Label smoothing parameter

z_j= ground-truth label

q_j= predicted probability

N =number of classes

4 Results

4.1 The process of training and validation

Before the proposed approach undergoes training, the entire set of data is processed in advance to boost the quality of the images and determine features for the training process. This processing applies to the Multi-Scale Retinex (MSR) method that attempts to improve image clarity by enhancing contrast and compensating for variations in brightness. By employing multiple Retinex scales, the MSR approach improves color fidelity and dynamic range compression, ensuring the training data is both consistent and transparent. This preprocessing step mitigates the impact of noise and non-uniform lighting, ultimately, enabling the model to learn only the key image features. Post-preprocessing, the model was trained on a workstation with following details:

- CPU: Intel Core i7
- GPU: 6 GB Nvidia GPU,
- RAM:16 GB
- Operating System: Windows 11
- Software: TensorFlow, Kera's on Python.

Training detail:

- Learning rate: 0.001
- Optimizer: Adam
- Number of epochs: 20
- Batch size: 32
- Input image size: 224x224

Figure 2 depicts the training and validation accuracy for the proposed model after training on above-mentioned parameters and setup. It is evident from the graphs that the model has learned the features without overfitting or under fitting.

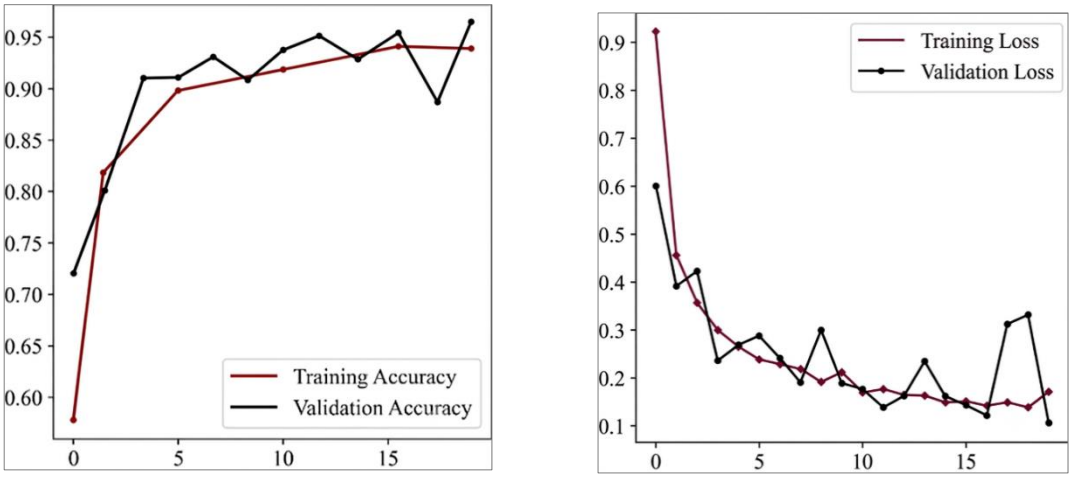

Figure 2: Performance of the proposed model on training dataset

As presented in Table 3, the model achieved an overall accuracy of 96%, reflecting its high proficiency in correctly classifying cases. This performance indicates that the model was able to make accurate predictions for the vast majority of instances, demonstrating its robustness and effectiveness as a classification tool. The strong accuracy score further suggests that the model can reliably distinguish between different classes while maintaining a low rate of misclassification.

The model exhibits potentially very promising performance for almost all the tissue classes, particularly it identifies the normal colon and normal lung tissues with a relatively high accuracy, achieving F1-scores of 97% and 99%, respectively. Other than normal cases, the model achieves an accuracy of 99% for colon adenocarcinoma. The model performs significantly well for rest of the classes as well. As shown in Table 3, the model attained F1-scores of 92% and 93% for lung adenocarcinoma and lung squamous cell carcinoma, respectively. However, these categories exhibited relatively lower precision and recall values compared with the other classes. Overall, the results highlight the efficacy and reliability of the proposed method for classifying different tissue types, with the strongest performance observed for normal tissues and colon adenocarcinoma.

Table 3: Overall performance of the model for all the classes in test dataset.

Name of the class	**Precision**	**Recall**	**F1-score**
Aca_Colon	99%	93%	96%
N_Colon	94%	99%	97%
Aca_Lung	95%	88%	92%
N_Lung	99%	99%	99%
Scc_Lung	89%	96%	93%
Overall Accuracy			**96%**

5 Conclusion

This study has demonstrated the efficacy of using a deep involution network along with a Multi-Scale Retinex algorithm. The proposed setup of deep learning model and image processing technique presented in the study has proved to achieve a tremendous success. The model successfully classifies lung and colon cancers. The model efficiently identifies and classifies the cancer types such as colon adenocarcinoma, colon normal, adenocarcinoma, squamous cell and carcinoma of the lungs. The proposed study uses a public dataset named LC25000. Despite the heterogeneous tumors of two dissimilar organs, the proposed model achieves a significantly better accuracy. The future extensions of this study may utilize Multi-Task learning models to further improve the performance by training the model on tumors of different types and tissues.

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