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Colorectal multi-class image classification using deep learning models

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ABSTRACT

Colorectal image classification is a novel application area in medical image processing. Colorectal images are one of the most prevalent malignant tumour disease type in the world. However, due to the complexity of histopathological imaging, the most accurate and effective classification still needs to be addressed. In this work we proposed a novel architecture of convolution neural network with deep learning models for the multiclass classification of histopathology images. We achieved the findings using three deep learning models, including the vgg16 with 96.16% and a modified version of Resnet50 with 97.08%, however the proposed Adaptive Resnet152 model generated the best accuracy of 98.38%. The colorectal image multiclass dataset is publicly available which has 5000 images with 8 classes. In this study we have increased all classes equally, total 15000 images have been generated using image augmentation technique. This dataset consists of 60% training images and 40% testing images. The suggested method in this paper produced better results than the existing histopathology image categorization methods with the lowest error rate. For histopathological image categorization, it is a straightforward, effective, and efficient method. We were able to attain state-of-the-art outcomes by efficiently utilizing the resourced dataset.

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1. INTRODUCTION

Colon cancer is one of the leading causes of death worldwide. According to the World Health Organization (WHO), there were estimated 1,849,519 new cases of colon cancer and 880,792 related deaths in 2018. Colorectal cancer is one of the most common cancers worldwide and one of the leading causes of cancer deaths [1]. In a study by the American Cancer Society, colorectal cancer was found to be one of the most common causes of cancer deaths in men and women. Therefore, the diagnosis of colon cancer becomes very important, especially in the early stages [2]. A reliable method to ensure that cancer is present in all parts of the body [3], [4]. Literature in the area of medical science has recorded evidence of this. However, there are only a few papers describing the most recent deep learning optimization accolades for histopathology images [5], [6]. Pathologists and clinical researchers have recognized and contributed to the use of histopathological imaging to detect tumours. However, this technique can be replaced by the new deep learning methods, for certain reasons which included traditional biopsy methods for diagnosing colon cancer are time-consuming and they require the prior knowledge of technicians, and the results may vary [7], [8]. Work experience of the pathologist is a crucial factor in the traditional diagnosis methods [9], [10]. Due to the recent advances in neural networks and image classification, convolutional neural networks (CNN) are now used to analyze histopathological images and classify cancer tissues [11], [12]. CNN has been a defining factor for classifying images and making decision in last few years [13], [14]. Since 2012 to 2019, when the ground breaking Alexnet, ImageNet, VGG16 and Resnet50, and other models [15], [16]. CNN has contributed to many advances in computer vision and image analysis, and histopathological imaging is one of the most important deep learning applications in the medical field [17], [18]. Much progress has been made in histopathological imaging, but there are not many studies on the classification of colorectal cancer imaging. Furthermore, many results of various studies still have unreliable accuracy results [19], [20]. In this paper, we aim to address the gap in colorectal cancer imaging in the existing review of literature. We used advanced deep learning CNN architectures such as Resnet152, Resnet50, and Vgg16 [21], [22]. A novel deep learning architecture with fine-tuning and image augmentation technique has been proposed to classify histopathological images, we used multi-class colorectal cancer image dataset. The proposed method experimented on the acquired dataset from the Kaggle database to evaluate the results.

The paper is organized is being as: section 2 contains the discussion on image augmentation technique, modified Resnet50, and Adaptive Resnet152. The augmented dataset showed good accuracy and low error rate after using the modified Resnet50 and adaptive Resnet152, section 3 includes results and discussion, we compared the results with different deep learning models.

2. PROPOSED METHOD

Resnet is one of the CNN architectures for large data sets. Compared with other types of neural networks, it still needs better competitive performance in classification [23]. The training method uses convolution neural network architecture [24], we use predictive model architecture, our goal is to improve performance by reducing bias and variance. This method effectively combines the predictions of each architecture involved in the evaluation to produce predictions. Robust CNN architectures [25], such as Resnet152, Resnet50, and VGG16 can be processed in a fully connected neural network to produce progressive results. The image augmentation method as shown in Figure 1, consists of image batches obtained from a separate neural network. According to the index, the trained CNN architecture is assigned non-linear weights, and the CNN model will be trained. Except for the fully connected layer and the dense layer, the CNN model is retrained with the last 10 layers frozen. Then use the colorectal histopathology dataset to train, validate, and test the final architecture.We proposed a novel CNN architecture to identify the lowest error rate and loss parameters. On the basis of performance indicators, the module was evaluated on measures such as accuracy, precision and recovery rate.

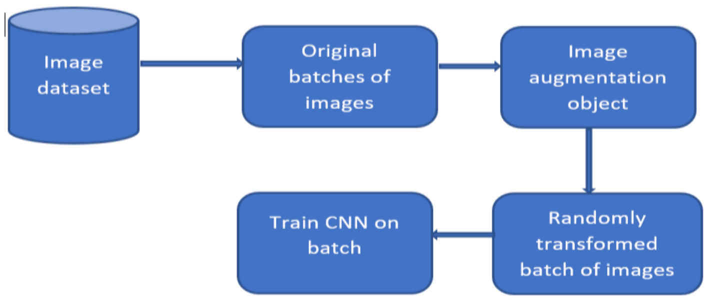

Figure 1. Basic architecture for image augmentation technique

This approach has been implemented when the imbalance of the upper class is an important factor; however, we use this data set to distribute the images class wise, reduce the performance complexity of a given architecture, and effectively optimize the model. CNN implementation:
We apply the convolution technique using the following equation:

$$G[M,N]=(F*H)[M,N]=\sum_j \sum_k H[j,k]F[M-j,N-K] \tag{1}$$

Where, input image is F, filter is H, M and N are represented indexes of rows and columns.
Resnet
It is two kinds of residual connections like F(x) and F(x)+x.

$$Y=F(x,\{W_i\})+x \tag{2}$$

$$Y= F(x, \{W_i\})+W_s x \quad (3)$$

The first equation is used when the both the input and output dimensions are same. The second equation is used when the both the dimensions are not same.

$$Z_j^{[i]} = \sum_{l=1}^{n} w_{j,l}^{[i]} a_l^{[i-1]} + b_j^{[i]} \quad (4)$$

where $a_j^{[i]} = \psi^{[i]}\left(z_j^{[i]}\right)$
In case where the skip connection is on, we have:

$$Z_j^{[i]} = \sum_{l=1}^{n} w_{j,l}^{[i]} a_l^{[i-1]} + b_j^{[i]} \quad (5)$$

where $a_j^{[i]} = \psi^{[i]}\left(z_j^{[i]} + a_j^{[i-2]}\right)$
With the right choice of the activation function $\psi^{[i]} w^{[i]}$ =0 and $b^{[i]} = 0$
We can have $a^i = a^{[i-2]}$ the residual block is capable of learning the identity function and thus it does not harm the neural network. We usually need a^i *and* $a^{[i-2]}$ to have the same shape so we use same convolution. If not, we set:$a^i = \psi^{[i]}(z^i + w_s a^{i-2})$ and dim $(w_s) = [n^i, n^{i-2}]$. Where W_s might be a fixed tensor or learned one.

2.1. Dataset

Colorectal histopathology images dataset is available in Kaggle.com. Submitted by the Kather *et al.*, 2019 [26], open source, including compressed files, composed of 5000 images, each image is 224×224 pixels, each image is reduced to 64×64 and eight classes are evenly distributed in non-overlapping categories such as tumour, stroma, complex, lympho, debris, mucosa, adipose, and empty. We had increased all the eight classes of generated images equally by using image augmentation technique. This dataset consists of total 20000 images and has multi-class tissue characteristics. Now, the 20000 colorectal histopathology images are splitted into 60% for training, 10% for validation and 30% for testing.

2.2. Modified Resnet50

Residual network (ResNet) is pretrained model. It is first proposed the concept of skip the connection. Figure 2 shows the transition connection as well as the stacking of convolution layers one after the other. In addition to the conventional stacking of the convolutional layer we also added the original input to the output of the convolutional block. The ResNet50 model is a pre-trained neural network, it has 5 stages, with a convolution block and an i- identification block. In Figure 2, each convolution block has 3 convolution layers, and each identification block also has 3 convolution layers ranging up to 23 million trainable parameters. We proposed this model for Colorectal cancer classification. Our proposed pretrained Resnet50 model uses freeze layers to add the output from an earlier layer to a later layer.

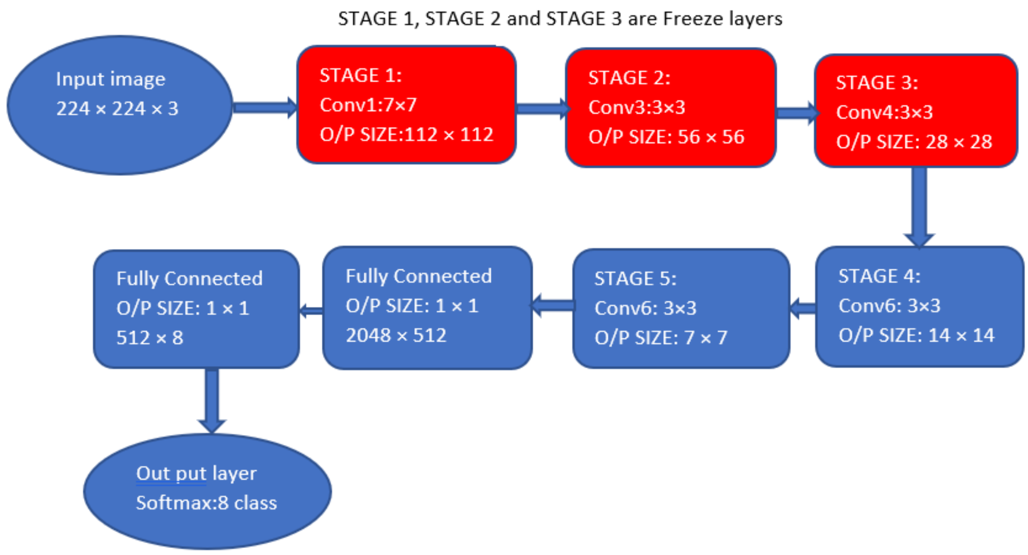

Figure 2. Architecture of Resnet50 freeze layer

2.3. Adaptive Resnet152

Resnet152 is 152 layers pretrained model. Which introduces the concept of residual learning, generally used for random access connections to learn feature subtraction at the input of this level. Residual training has proven to improve the performance of model training. Resnet152 has over 23 million parameters. Our proposed pretrained Resnet152 model uses the input image 224×224 pixels it passed to 6 convolution blocks. Each block had a filter size 3×3 with stride value 2 i.e., Figure 3. Resnet152 produces low error rate and it improve the model performance. We used the same dataset for Resnet152 architecture model. Which was executed with colorectal cancer image dataset with 60% training, and 30% testing and 10% for validation.

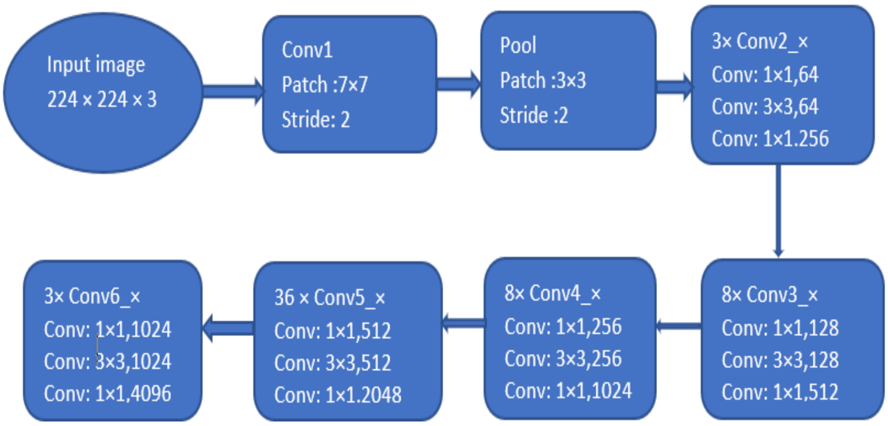

Figure 3. Basic architecture of Resnet152 with 6 convolution blocks

3. RESULTS AND DISCUSSION

In this research, we experimented on 8 models, each model is tested on the same dataset. However, we reconstructed and demonstrated the performances of individual model. It can be visualized for the eight classes of colorectal cancer images which is shown in Figure 4. The eight classes are Tumor, Stroma, Complex, Lympho, Debris, Mucosa, Adipose, and Empty.

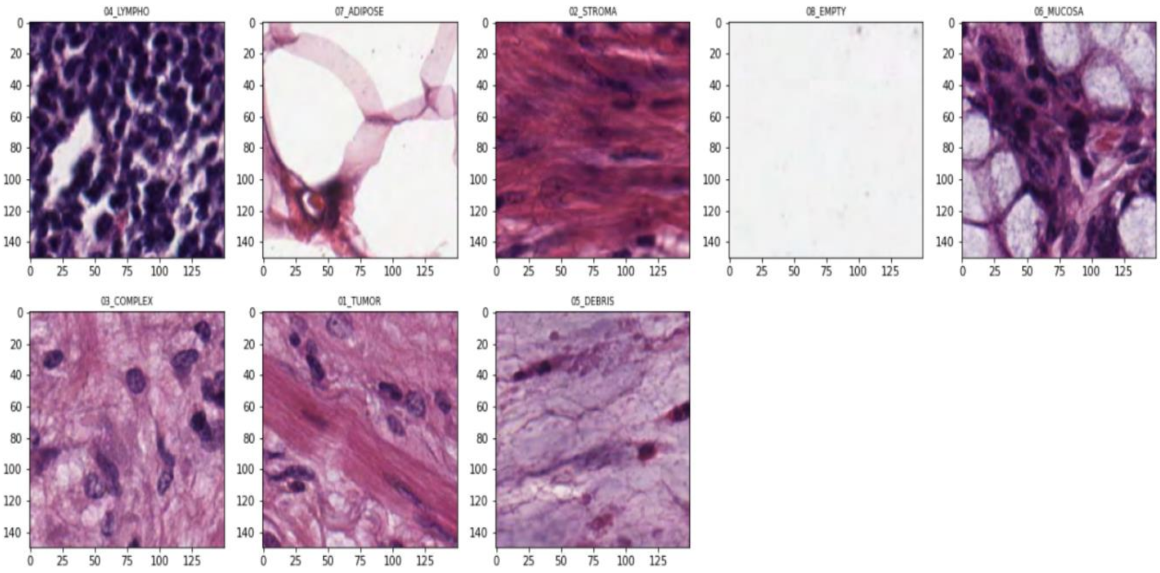

Figure 4. Representation of 8-multiclass colorectal histopathology images

In our trained CNN design, the trained model was divided into 2 major parts. In the 1st phase we have a tendency to trained individual architectures with pretrained individual models like Resnet152, Resnet50, VGG16, and the configurable architecture of the CNN model. In the second phase, we checked the results obtained from the creation of a single model and a CNN. The performance of our proposed method is compared with the existing methods.

The performance analysis of eight individual models is shown in Figure 5. Finally, we compared results that had a classification of test accuracy of more than 90%. Individual performance accuracy for Resnet152, Resnet50, and VGG16 is 98.38%, 97.08%, and 96.14%, respectively, and the images are accurately identified. The comparative results are shown in Table 1. The proposed adaptive Resnet152 achieved better accuracy rate of 98.38% and lowest error rate compared to existing models. These results show the effectiveness of the proposed method.

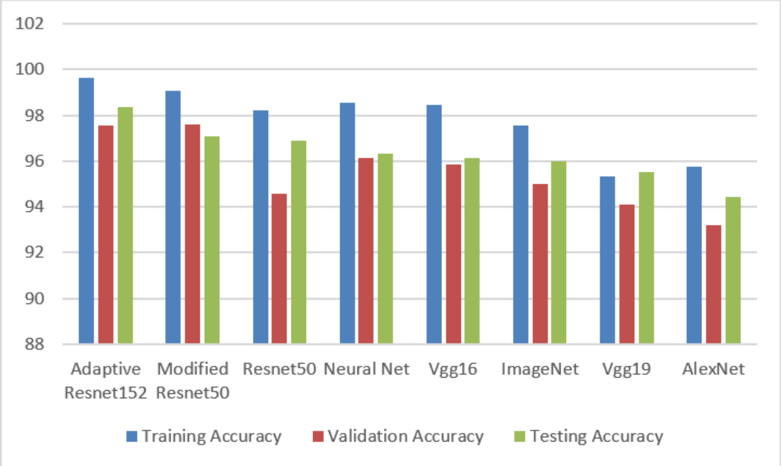

Figure 5. Graphical representation of comparative results

Table 1. Comparative results of histopathology cancer images multi-class classification

S.NO.	No. of Epochs	Models	Training accuracy	Validation accuracy	Testing accuracy
1	30	Adaptive Resnet152	99.65	97.53	98.38
2	30	Modified Resnet50	99.05	97.62	97.08
3	30	Resnet50	98.22	94.55	96.89
4	30	Neural Net	98.53	96.13	96.34
5	30	Vgg16	98.43	95.83	96.14
6	30	ImageNet	97.55	95.02	95.98
7	30	Vgg19	95.35	94.10	95.53
8	30	AlexNet	95.75	93.2	94.45

4. CONCLUSION

In this paper, we proposed a deep conventional neural network model for multi class classification of colorectal histopathology images. The last ten layers of network are feezed and re-trained the main neural network with dense layer. We successfully improved the accuracy for classification of multi class colorectal histopathology images. Through adaptation of the Resnet152 and reconstruction of Resnet50 models, we trained the CNN architecture for best classification accuracy 98.38% and lowest error rate. These results lead to reliable disease identification tumour from colorectal histopathology images. The results acquired were arguably more sophisticated than the currently existing models. In the future work, we are planning to use transfer learning method to obtain better results.

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