A Comparative Study of ResNet and DenseNet in the Diagnosis of Colitis Severity

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Abstract. The current diagnostic approaches for assessing the severity of colitis necessitate medical professionals or specialists to subjectively evaluate colitis colonoscopy images, relying extensively on their clinical expertise. The accuracy of these assessments is of utmost importance in guiding subsequent treatment strategies for individuals with colitis. Several deep learning models have demonstrated their efficacy in the domain of medical imaging, serving as dependable tools for visualizing and analyzing medical data. These models include deep learning-based models and convolution-based neural network models. This study aimed to assess the effectiveness of various convolution-based neural network models in diagnosing the severity of colitis. Specifically, the representative ResNet and DenseNet models were chosen for a comparative analysis. Four types of medical imaging images of colitis with different severity were selected for classification and diagnosis. The experimental results demonstrate that DenseNet outperforms ResNet in terms of efficiency and accuracy for diagnosing colitis severity. DenseNet achieves an accuracy rate of up to 80%, indicating the promising potential for its application in the field of medicine.

Keywords: ResNet · DenseNet · Deep Learning · Colitis · Diagnosis

1 Introduction

Colitis is a pathological condition characterized by inflammation, which can be attributed to a multitude of etiological reasons. Diagnosis and treatment of colitis typically necessitate consideration of several aspects during the patient's visit. The incidence of consultations for colitis has had an upward trend in recent years. Nevertheless, it is important to acknowledge that the extent of colitis may be overestimated during the initial consultation, and failure to administer appropriate and timely treatment poses a significant risk of infection transmission, thereby significantly impacting the patient's overall well-being. Hence, it is

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imperative to precisely assess the extent of colitis by utilizing colonoscopy pictures during the initial stages of diagnosis with utmost accuracy and efficiency. This is crucial to prevent the potential issue of delayed therapy resulting from an underestimation of the patient's condition severity.

The diagnostic techniques commonly employed in medical practice to assess the severity of colitis typically involve the utilization of colonoscopy and mucosal biopsy. Colonic mucosal lesions are typically identified by physicians who rely on their own detection ability and clinical expertise. However, the reliance on clinicians alone for judging the severity of colitis is often seen as insufficient in terms of trustworthiness. The progressive advancement of deep learning is progressively emerging as a significant tool and instrument for paramedical care. Various deep learning models have demonstrated consistent performance in terms of their ability to withstand recognition and control systems, as well as exhibit rapid convergence [1,2]. In their study, Harada et al. [3] introduced a semi-supervised learning approach to categorize endoscopic images of colitis. Neural networks have been extensively utilized by researchers to classify medical images of diseases, including colitis [4,5]. These studies have demonstrated the effectiveness of employing deep learning techniques for the classification of colonoscopic images of colitis, thereby validating their potential utility in the clinical management of this condition.

In the realm of image classification, ResNet and DenseNet have demonstrated notable efficacy and achieved favorable outcomes. In their study, Sarwinda et al. [6] introduced a method for detecting colorectal cancer by employing ResNet-18 and ResNet-50 models, which yielded promising results in terms of accuracy. The DenseNet model has demonstrated exceptional performance in various domains such as daily life, agricultural output, and medical diagnostics. The severity of diabetic retinopathy was assessed using DenseNet by the authors in the paper [7]. The study conducted by the authors in reference [8] employed DenseNet as a methodology for the identification and categorization of diseases in tomato plant leaves.

This study aims to investigate the potential of deep learning in diagnosing disease severity and enhancing the performance of the colitis severity diagnostic model. To achieve this, the research employs two deep learning models, namely ResNet and DenseNet, for comparative analysis. Experimental evaluations are conducted to analyze the diagnostic outcomes of both models. The primary contributions of this study are as follows:

1. This study examines the disparities and dependability of two prominent convolution-based deep learning techniques, namely ResNet and DenseNet, within the domain of colitis severity diagnosis. The two models categorize colonoscopy images into four types based on the severity of colitis. This classification enhances the effectiveness of diagnosing colitis severity, minimizes the likelihood of subjective errors made by clinicians, and offers a framework for future investigations in the field of colitis severity diagnostic models.
2. A comparison analysis was conducted to assess the efficacy and performance of ResNet and DenseNet models in diagnosing the severity of colitis. The

study aimed to investigate the underlying mechanisms and classification accuracy of colonoscopy images using these two models. Subsequent investigations have demonstrated that DenseNet outperforms ResNet in the classification of colonoscopy images. This superiority is manifested not only in improved diagnosis accuracy but also in its superior generalization capabilities and processing economy.

2 Approach

2.1 The Diagnosis of Colitis Using a ResNet-Based Approach

The deep residual network (ResNet) is a deep learning model that was developed by He et al. [9]. Their research findings indicate that ResNet exhibits superior performance compared to other models in the task of image categorization. ResNet, in comparison to alternative deep learning models, effectively addresses the challenge of gradient vanishing or gradient explosion that arises from the deep network architecture by employing a residual structure. Additionally, ResNet exhibits reduced training time and computing cost, along with enhanced training capabilities.

The feature extraction process of the plain network may be demonstrated by utilizing the LIMUC dataset as the initial input data for training the model [10]

$$x_m = \sigma\left(\sum_{i=0}^{m} w_i x_i + \theta\right) \tag{1}$$

The symbol σ represents the non-linear activation function utilized in the neural network. The variable w_i represents the weight information associated with the colitis colonoscopy image, whereas x_i is the input data of said image. Lastly, θ denotes the bias term. To enhance the depth of the network while mitigating the issue of gradient explosion, the plain network incorporates a residual structure. The residual block can be created for every deep unit by employing recursive techniques. L characteristics are manifested as [9]

$$\mathrm{x_L} = \mathrm{x_1} + \sum_{\mathrm{i=1}}^{\mathrm{L-1}} \mathrm{F}(\mathrm{x}_i, W_i) \tag{2}$$

In this context, L represents the unit layer of the neural network. $\mathrm{F}(\cdot)$ represents the mapping relation of the residual structure. x_L refers to the output of the unit in the layer L, and x_i refers to the input of the unit in the layer i. In the context of backpropagation, given that the loss function is denoted as E, the application of the chain rule allows us to obtain the desired outcome

$$\frac{\partial E}{\partial \mathbf{x}_1} = \frac{\partial E}{\partial \mathbf{x}_L}\frac{\partial \mathbf{x}_L}{\partial \mathbf{x}_1} = \frac{\partial E}{\partial \mathbf{x}_L}\left(1 + \frac{\partial}{\partial \mathbf{x}_1}\sum_{\mathrm{i=1}}^{\mathrm{L-1}} F(\mathbf{x}_\mathrm{i}, \mathbf{w}_\mathrm{i})\right) \tag{3}$$

The chain rule of backpropagation can be conceptually separated into two components. The first component involves the propagation of data signals without involving weight layers, which can be denoted as $\frac{\partial E}{\partial \mathbf{x_L}}$. This process allows for the direct passage of data signals back to any shallow structure. The second component involves the propagation of data signals through weight layers, which can also be represented as $\frac{\partial E}{\partial \mathbf{x_L}}(\frac{\partial}{\partial \mathbf{x_1}}\sum_{i=1}^{L-1} F(\mathbf{x_i}, w_i))$. $\frac{\partial E}{\partial \mathbf{x_L}}(\frac{\partial}{\partial \mathbf{x_1}}\sum_{i=1}^{L-1} F(\mathbf{x_i}, w_i))$. This latter component ensures that the neural network model does not encounter the issue of vanishing gradient, as the resulting value cannot be equal to -1. In conclusion, the results generated by the Resnet-based colitis diagnostic network can be represented as

$$\begin{aligned} y = Softmax(&F_L(R_{L-1}(F_{L-2}(\dots(R_2(F_1(x; W_1, b_1)) + x_2; W_{R2}, b_{R2})\dots) \\ &+ x_{L-1}; W_{L-1}, b_{L-1})) + x_L; W_L, b_L) \end{aligned} \tag{4}$$

In this context, the variable represents the severity of the colonists as recognized by the network by colonoscopy imaging. Additionally, Ri specifies the layer i residual block. The diagram illustrating the ResNet-based diagnostic model for assessing the severity of colitis is depicted in Fig. 1.A.

2.2 The Diagnosis of Colitis Using a DenseNet-Based Approach

The DenseNet model, initially introduced by G Huang et al. [11], is characterized by its dense connectivity. The DenseNet architecture incorporates the DenseBlock-Transition structure, which facilitates the connection of features across layers rather than relying on a linear mapping relationship. By utilizing colonoscopy images depicting colitis as the input data for model recognition, it is possible to articulate the relationship between the features of the input and the corresponding output [12].

$$X(t) = H([X0, X1, X2, ..., X(t-1)]) \tag{5}$$

Let $X(t)$ represent the output of layer t. $X0, X1, X2, ..., X(t-1)$ refer to the input data preceding layer t. H signifies the non-linear transformation applied to each DenseBlock. A DenseBlock refers to a module of many levels, wherein the feature maps of each layer possess identical dimensions. The Transition module serves the purpose of connecting two adjacent DenseBlocks, facilitating the reduction in the size of feature maps and ensuring their compatibility in terms of dimensionality through the utilization of Pooling. The diagnostic identification of four distinct forms of colitis with varying degrees of severity can be achieved by the utilization of the softmax function.

$$\begin{aligned} y = \mathrm{Softmax}(&F_{\mathrm{output}}(F_{\mathrm{avg-poo1}}((F_{db}(x; W_{db}, b_{db})); W_{\mathrm{avg-poo1}}, b_{\mathrm{avg-poo1}}); \\ &W_{\mathrm{output}}, b_{\mathrm{output}}) \end{aligned} \tag{6}$$

where y denotes the probability distribution of the outcome of the prediction of the severity course of colitis colonoscopy. F_{output} denotes the last fully connected layer of the model, the W_{output} and b_{output} denote their corresponding weights and biases. $F_{\text{avg-pool}}$ denotes the average pooling layer of the model, and its corresponding associated weights and biases are $W_{\text{avg-pool}}$ and $b_{\text{avg-pool}}$. F_{db} denotes the different DenseBlocks, and the corresponding weights and biases of each DenseBlocks are W_{db} and b_{db}. The resulting DenseNet-based diagnostic model for colitis severity is shown in Fig. 1.B.

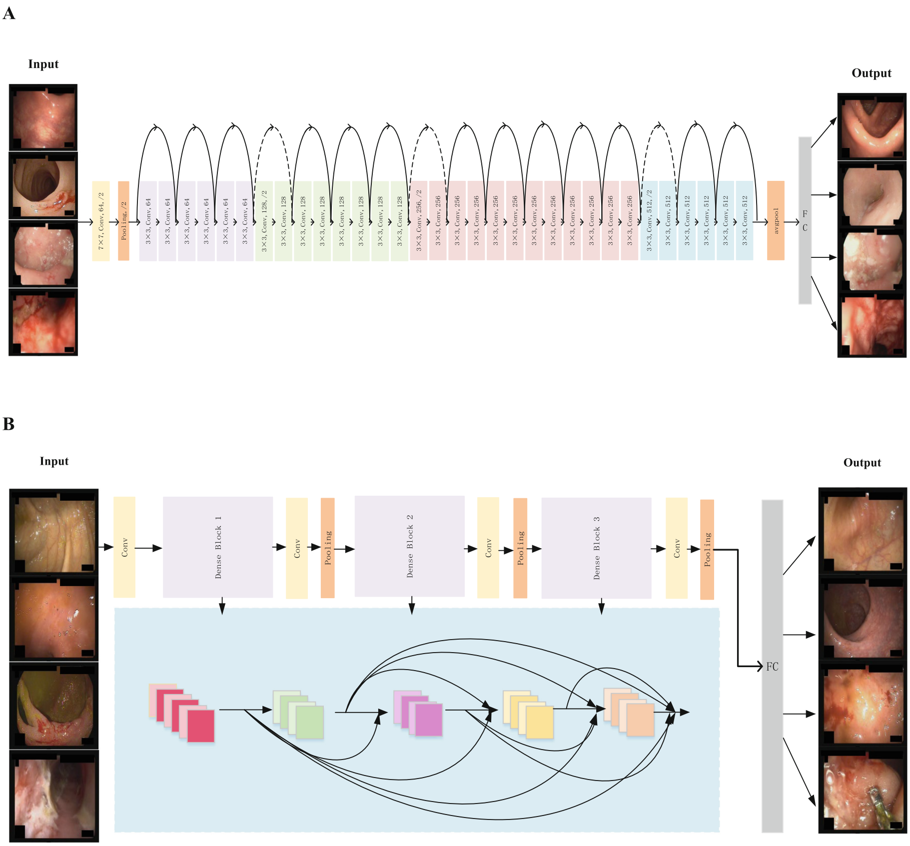

Fig. 1. A is the diagnosis of colitis using a ResNet-based approach; B is the diagnosis of colitis using a DenseNet-based approach

3 Experiments

The experimental patients for this investigation were picked from the LIMUC dataset [13], consisting of colonoscopy pictures depicting various colitis disorders. These diseases were classified into four severity classifications, namely Mayo 0, Mayo 1, Mayo 2, and Mayo 3. Out of the total 7502 data photos belonging to various classes, around 80% of these images, amounting to around 6000, were utilized as the training set in the conducted trials. Approximately 20% of the total number of photos, specifically around 1500 images, were allocated for utilization as the test set. To ensure equal representation of images for colitis illness identification in each acquisition, a consistent batch size of 16 was employed for the tests.

To assess the precision of the two network models in detecting colitis disease in colonoscopy images, we conducted tests on ResNet, and DenseNet, and pre-trained processed ResNet and DenseNet. As depicted in (a) of Fig. 2, the maximum accuracy achieved by the pre-trained DenseNet model is around 80%, while the maximum accuracy attained by the DenseNet model without pre-training is approximately 76%. The maximum accuracy achieved by the pre-trained ResNet model is approximately 73%, while the maximum accuracy attained by the ResNet model without pre-training is approximately 71%. The analysis demonstrates that DenseNet diverges from the conventional approach of increasing the depth and width of network layers to enhance model performance, as observed in ResNet. Instead, DenseNet achieves this by reducing the number of network parameters through the utilization of feature reuse and bypass mechanisms. This design choice not only facilitates training in comparison to ResNet but also yields a certain degree of regularisation effect. The pre-trained model has superior overall performance compared to the non-pre-trained model. Additionally, in the context of colitis illness detection, the pre-trained DenseNet exhibits faster convergence and more accurate analysis and identification of the severity of the disease.

The boxplot in Fig. 2(b) demonstrates that DenseNet exhibits superior performance compared to ResNet in terms of stability and accuracy across multiple experiments. This can be attributed to DenseNet's effective utilization of feature reuse, which prevents excessive weight shifting during training iterations. Consequently, the weights in DenseNet remain more stable throughout the training process, leading to improved overall stability when compared to the ResNet model.

Figure 2(c) compares the loss values of ResNet, DenseNet, and pre-trained processed ResNet and DenseNet in the context of feature detection in colitis colonoscopy images. The results indicate that DenseNet exhibits a notable advantage over ResNet in terms of both image feature detection and model robustness. Furthermore, the pre-trained DenseNet demonstrates superior capability in feature extraction specifically in the context of colitis. The pre-trained DenseNet demonstrates superior capability in extracting features from colitis colonoscopy images.

In Fig. 2(d), the histogram illustrates the minimum loss observed in colitis enteroscopy images for pathology detection using various models. The figure demonstrates that DenseNet, with its feature reuse and dense connectivity, effectively reduces the image loss in each iteration. Specifically, the loss value in colitis enteroscopy images can be reduced to approximately 0.5 for DenseNet without pre-training. Additionally, the pre-trained model exhibits a further reduction in loss value. The loss value of the pre-trained DenseNet model is 0.234. The untrained ResNet has a loss value of 0.347, whereas the pre-trained ResNet demonstrates a loss value almost equal to 0.239. The utilization of a pre-trained model has the potential to enhance the precision of picture classification and detection. Additionally, it can concurrently diminish the loss value associated with the identified image, as evidenced by the data presented in Fig. 2. While both pretrained DenseNet and ResNet exhibit identical loss outcomes, it is noteworthy that DenseNet demonstrates a greater accuracy. This observation suggests that DenseNet possesses superior robustness and generalization capabilities in comparison to ResNet.

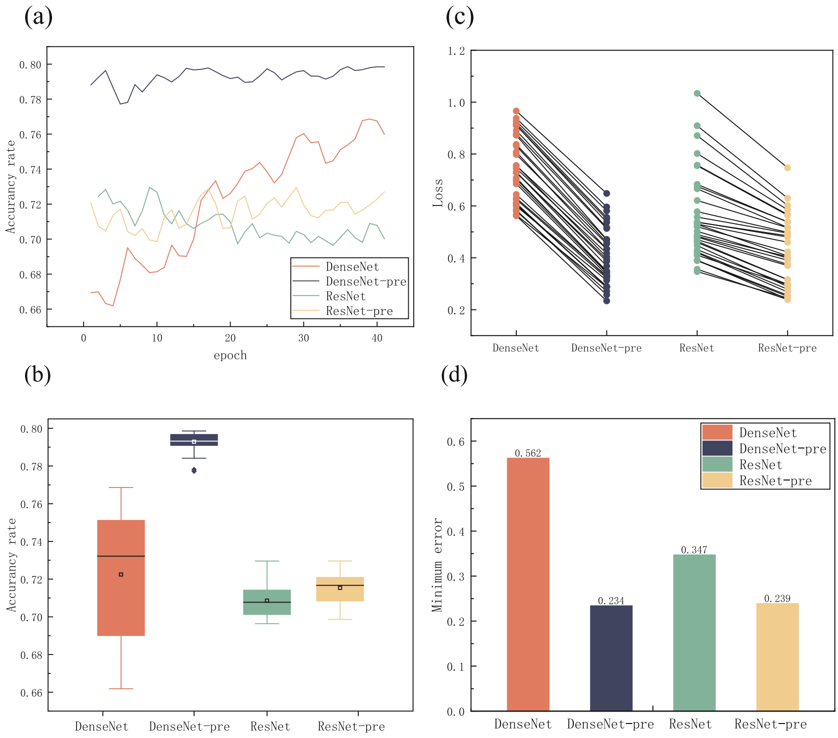

Fig. 2. (a) denotes the accuracy plot of ResNet and DenseNet under the LIMUC dataset; (b) denotes the boxplot obtained from multiple experiments of ResNet and DenseNet; (c) denotes the loss comparison between pre-trained and untrained ResNet and DenseNet; and (d) denotes the loss bar graph of ResNet and DenseNet loss histogram for LIMUC dataset detection

4 Conclusion

This study aimed to compare the performance of the two representative convolution based deep learning models, ResNet and DenseNet, in colonoscopy image classification. A series of comparative experiments were conducted to determine the viability of the two models in the diagnosis of colitis severity. According to the experimental results, DenseNet not only has a slight improvement in accuracy to reach 80% on colonoscopy images of colitis but also has a higher training efficiency of the model, which can reach convergence at a faster rate. ResNet and DenseNet both have strong feature extraction capabilities and image classification advantages. Therefore, DenseNet performs satisfactorily and has more advantages over ResNet in terms of diagnostic accuracy and robustness when it comes to determining the severity of colitis.

The comparative study may further examine the diagnostic performance and accuracy of the two models for colitis severity diagnosis. The deep learning model has the potential to be further developed in the diagnosis of the severity of colitis, as evidenced by the positive results of ResNet and DenseNet. Clinicians can use it as a practical tool to create personalized treatment plans that take into account the unique circumstances of each patient. Further investigation into ResNet and DenseNet will be carried out to address further obstacles in the processing of colonoscopy images from enterocolitis. To continuously enhance the performance of the colitis severity diagnostic model, more deep learning models will be tested and modified in this direction in the future. In the meantime, the application of deep learning models to the diagnosis of colitis severity has a promising development space.

References

1. Liu, K., Wang, R.: Antisaturation adaptive fixed-time sliding mode controller design to achieve faster convergence rate and its application. IEEE Trans. Circuits Syst. II Exp. Briefs **69**(8), 3555–3559 (2022)
2. Liu, K., Yang, P., Wang, R., Jiao, L., Li, T., Zhang, J.: Observer-based adaptive fuzzy finite-time attitude control for quadrotor UAVs. IEEE Trans. Aerosp. Electron. Syst. **59**(6), 8637–8654 (2023). https://doi.org/10.1109/TAES.2023.3308552
3. Harada, S., Bise, R., Hayashi, H., Tanaka, K., Uchida, S.: Order-guided disentangled representation learning for ulcerative colitis classification with limited labels. In: de Bruijne, M., et al. (eds.) MICCAI 2021. LNCS, vol. 12902, pp. 471–480. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-87196-3_44
4. Alammari, A., Islam, A.R., Oh, J., Tavanapong, W., Wong, J., De Groen, P.C.: Classification of ulcerative colitis severity in colonoscopy videos using CNN. In: Proceedings of the 9th International Conference on Information Management and Engineering, pp. 139–144 (2017)
5. Bhambhvani, H.P., Zamora, A.: Deep learning enabled classification of mayo endoscopic subscore in patients with ulcerative colitis. Eur. J. Gastroenterol. Hepatol. **33**(5), 645–649 (2021)
6. Sarwinda, D., Paradisa, R.H., Bustamam, A., Anggia, P.: Deep learning in image classification using residual network (ResNet) variants for detection of colorectal cancer. Procedia Comput. Sci. **179**, 423–431 (2021)
7. Farag, M.M., Fouad, M., Abdel-Hamid, A.T.: Automatic severity classification of diabetic retinopathy based on DenseNet and convolutional block attention module. IEEE Access **10**, 38299–38308 (2022)

8. Albahli, S., Nawaz, M.: DCNet: DenseNet-77-based CornerNet model for the tomato plant leaf disease detection and classification. Front. Plant Sci. **13**, 957961 (2022)
9. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778 (2016)
10. Kiranyaz, S., Avci, O., Abdeljaber, O., Ince, T., Gabbouj, M., Inman, D.J.: 1D convolutional neural networks and applications: a survey. Mech. Syst. Sig. Process. **151**, 107398 (2021)
11. Huang, G., Liu, Z., Van Der Maaten, L., Weinberger, K.Q.: Densely connected convolutional networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 4700–4708 (2017)
12. Zhang, C., et al.: ResNet or DenseNet? Introducing dense shortcuts to ResNet. In: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 3550–3559 (2021)
13. Polat, G., Kani, H., Ergenc, I., Alahdab, Y., Temizel, A., Atug, O.: Labeled images for Ulcerative Colitis (LIMUC) dataset, March 2022