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ORIGINAL RESEARCH

Diagnosis of Irritant Dermatitis in Colorectal Cancer Postoperative Stoma Patients Using Smartphone Photographs: A Deep Learning Approach

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Background: Irritant dermatitis is a common complication among stoma patients, significantly impacting their quality of life. Early diagnosis is essential, but limited access to healthcare and poor self-management skills often delay treatment. This study aimed to assess the effectiveness of two advanced convolutional neural networks (CNNs), ConvNeXt and MobileViT, for the intelligent diagnosis of irritant dermatitis using smartphone-acquired stoma images.

Methods: A retrospective observational study was conducted, collecting 825 stoma complication images from five tertiary hospitals in China. Data preprocessing techniques such as resampling and enhancement were used to prepare the dataset. The ConvNeXt and MobileViT models were trained and evaluated based on accuracy, precision, recall, and F1 scores. Optimizers and learning rates were also adjusted to assess model performance.

Results: ConvNeXt demonstrated superior performance, achieving an accuracy of 71.4%, precision of 73.6%, recall of 67.1%, and an F1 score of 70.2% with the Adam optimizer and a 0.001 learning rate. MobileViT, despite being more lightweight, did not surpass ConvNeXt, with a maximum accuracy of 64.4%. ConvNeXt excelled in diagnosing irritant dermatitis and normal stoma conditions but showed limitations in recognizing other complications.

Conclusion: The ConvNeXt model outperformed MobileViT, indicating that advanced CNNs can effectively assist in the early diagnosis of irritant dermatitis among stoma patients. This could help alleviate the burden on healthcare resources and improve patient outcomes through accessible mobile-based diagnostic tools.

Keywords: stoma patients, irritant dermatitis, convolutional neural networks, artificial intelligence

Introduction

Colorectal cancer ranks as the third most common cancer globally in terms of incidence and second in mortality, affecting over 1.9 million individuals with approximately 902,100 deaths in 2022.[1] Surgery remains the cornerstone of treatment for colorectal cancer.[2] To mitigate the risk of anastomotic leakage and preserve excretory function post-operatively, the surgical establishment of an intestinal stoma is often necessitated.[3] It is estimated that over 750,000 people in the United States and more than one million in China have an ostomy.[4,5] Peristomal skin complications (PSCs) are a significant concern for individuals living with an ostomy, presenting as one of the main post-operative challenges that affect patients' quality of life and necessitate comprehensive management strategies.[6] It was shown that about 80% of patients with stoma experience PSCs, with irritant dermatitis being the most common.[7]

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Irritant dermatitis is primarily caused by direct contact between the skin and stoma secretions, including feces or urine.[8] This exposure leads to skin irritation due to the enzymatic activity and chemical composition of the effluent. Key factors contributing to the onset of irritant dermatitis include improper fitting of the ostomy appliance, leading to leakage, inadequate protection of the peristomal skin, and the high output nature of some stomas, particularly those with liquid consistency.[9] The ramifications of irritant dermatitis are not to be understated, as they encompass an escalated risk of secondary infections, considerable pain, and discomfort, alongside potential impediments to effective stoma care, such as impaired skin healing and difficulties in maintaining an optimal appliance fit.[10] Therefore, early diagnosis of irritant dermatitis becomes crucial to effectively curb the progression of the lesion. However, due to the lack of adequate self-management skills and continuous medical follow-up, it is often difficult for out-of-hospital stoma patients to recognize the early signs of irritant dermatitis in a timely manner, resulting in deterioration of the condition by the time the enterostomal therapist intervenes, increasing the risk of unplanned readmission and financial toxicity for the patient.[8,11,12] In addition, the number of stoma patients worldwide shows a continuous growth trend, while there is a shortage of human resources for enterostomal therapists.[13] This makes it difficult for stoma patients to easily access professional and quality healthcare services, and poses a challenge for the early diagnosis of irritant dermatitis. Consequently, facilitating the inclusivity of medical services through technological means to enable the early diagnosis of irritant dermatitis in stoma patients has emerged as a question worthy of exploration.

With the rapid development of artificial intelligence technology, it has become a research hotspot to realize disease diagnosis by applying machine learning and deep learning algorithms to feature extraction of medical images.[14] Among various deep learning architectures, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for the intelligent diagnosis of medical images, attributed to their superior capabilities in image analysis and classification.[15] The accuracy of CNN in the early diagnosis of conditions such as skin cancer, diabetic foot, and pressure injury matches or exceeds that of human experts.[16–18] This underscores the potential of CNN technology not only in enhancing early disease diagnostic accuracy but also in offering a pathway to bridge the gap in healthcare services for stoma patients. Andersen et al used CNN to monitor the development of discolored skin and leakage over time in real time by intelligently analyzing peristoma images, facilitating accurate assessment and timely disposition by enterostomal therapists.[19] However, this study primarily utilized images depicting discoloration and leakage around the stoma for training, focusing on an objective representation of skin conditions rather than directly diagnosing irritant dermatitis. Moreover, Andersen et al used the VGG-16 algorithm, which has limitations such as large number of parameters, long computation time, and difficult deployment.[20] These factors hinder its integration with mobile platforms, thus limiting its utility in the home stoma patient setting. With the development of various new techniques for efficiently training deep networks, new CNNs with improved performance have emerged, such as ConvNeXt and MobileViT. Unlike traditional models that prioritize depth and complexity, ConvNeXt introduces optimizations in convolution operations, aiming to balance performance with computational efficiency.[21] On the other hand, MobileViT embodies the fusion of convolutional approaches with the transformer architecture, targeting a lightweight model without compromising on diagnostic accuracy.[22] These developments signify a shift towards models that are not only accurate but also adaptable to resource-constrained environments.

The aim of this study was to evaluate the effectiveness of these advanced CNNs in the intelligent diagnosis of irritant dermatitis among stoma patients. By comparing two state-of-the-art CNNs, ConvNeXt and MobileViT, the most effective real-time, accessible diagnostic models are identified, thus providing promising solutions for empowering patients for early diagnosis and alleviating the shortage of enterostomal therapists. This study contributes a new method for diagnosing irritant dermatitis in patients with stoma and helps to advance the use of AI in healthcare and promote access to healthcare.

Method

Design

This study employed a retrospective observational design. Medical images of stoma-related complications were collected from January to April 2024 across five grade A tertiary hospitals in China. Based on these archived color images, we developed a deep learning model to assist in the diagnosis of irritant dermatitis and conducted a comparative evaluation of model performance. The overall methodological framework is illustrated in Figure 1.

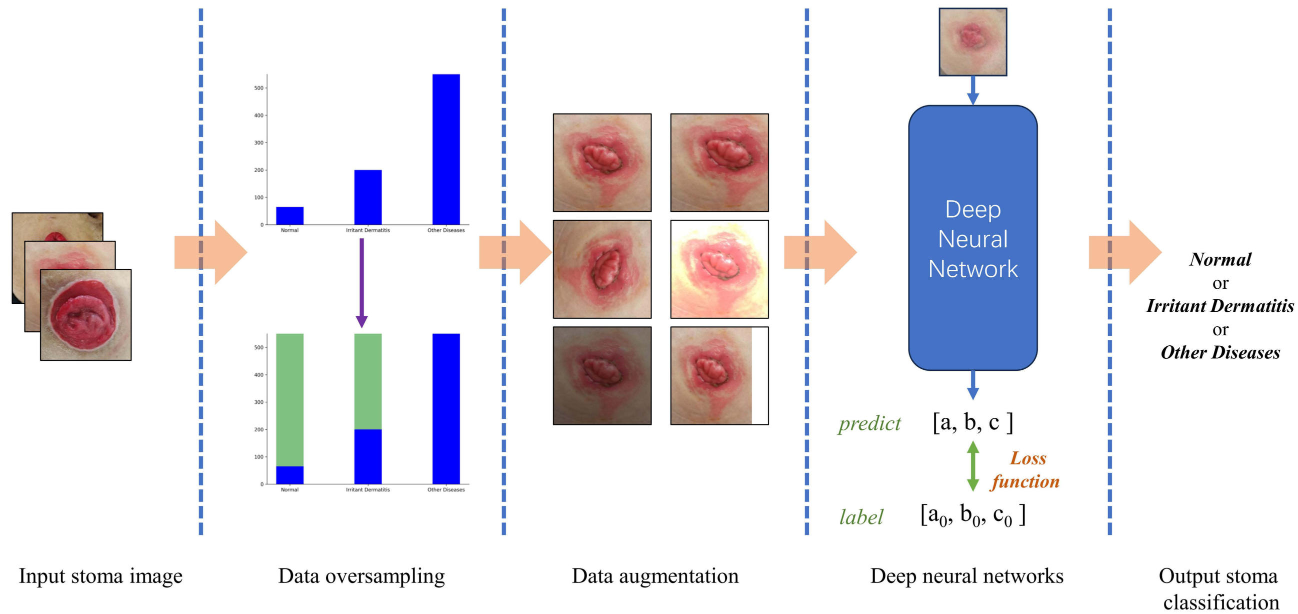

Figure 1 Workflow of the deep learning-based stoma image classification pipeline. The figure illustrates the step-by-step process of the proposed model development, beginning with the input of smartphone-captured stoma images. The workflow includes data preprocessing stages such as data oversampling to address class imbalance and data augmentation to increase dataset diversity. Images are then fed into a deep neural network, which outputs a probability vector [a, b, c] representing the predicted likelihoods for each class. The true class labels are represented by $[a_0, b_0, c_0]$. The model is trained by minimizing the Loss function, which measures the difference between predicted outputs and true labels. The final output is a classification result into one of three categories: Normal, Irritant Dermatitis, or Other Diseases, as shown at the end of the pipeline.

Process of Building the Dataset

In collaboration with five grade A tertiary hospitals located in Beijing, Shenyang, Changchun, and Taiyuan, we retrospectively collected a total of 825 smartphone-captured stoma images from clinical records. All images were acquired following a standardized imaging protocol to ensure consistency. The dataset was categorized into Normal Stoma (n=65), Irritant Dermatitis (n=200), and Other Complications (n=560). Each image underwent double-blind review by certified enterostomal therapists, and in cases of disagreement, a third expert provided adjudication.

All personal and identifying information was removed or anonymized to ensure patient confidentiality. To address class imbalance and enhance model generalizability, we conducted data preprocessing procedures including resampling and data augmentation techniques (eg, random flipping, scaling). After reserving 30 images per category for testing, the remaining images were used to train the deep learning models.

Experimental Model

The experiment involved training with various neural networks, including ConvNeXt and Mobilevit.

ConvNeXt is a convolutional model designed to compete with Transformers in accuracy and scalability by incorporating enhancements from Transformer-based and convolution-based architectures.[21] It features a multi-stage design with varied feature map resolutions, a simplified "Patchify" layer replacing traditional stem cells, and grouped convolution to align channel numbers and widen the network. The model uses large 7×7 convolution kernels to improve performance and applies Layer Normalization and GELU activation to enhance efficiency and reduce computational demands. ConvNeXt also introduces Layer Scale and Drop Path techniques to stabilize deep network training and mitigate vanishing gradients, supporting effective deep network stacking with consistent input and output dimensions across blocks.

MobileViT is a novel, lightweight network that combines the Vision Transformer (ViT) model's self-attention mechanism with MobileNet's efficient architecture to reduce computational demands and parameter count, making it ideal for mobile systems.[23] It utilizes deep separable convolution to optimize resource usage without compromising performance, particularly enhancing image classification accuracy and model interpretability for complex scenes. The

MobileViT architecture consists of MobileNetV2 and MobileViT Blocks. The MobileNetV2 Block processes data through layers of convolution and batch normalization, utilizing ReLU6 for activation, which is optimized for low-precision mobile computations. The MobileViT Block manipulates feature maps through a series of transformations, including unfolding into sequences, processing via a Transformer architecture to capture global dependencies, and refolding to integrate learned features back into the spatial domain. This structure enables effective feature extraction and integration, ensuring robust performance in visual tasks.

Evaluation

In this study, we use accuracy, precision, recall, and the F1-score as our evaluation metrics to assess the precision of our stoma classification. We consider four key components in our evaluation: True Positives (TP), False Negatives (FN), False Positives (FP), and True Negatives (TN). Each of these evaluation indicators is explained in detail as follows:

Accuracy

Accuracy is an index to measure the overall prediction result of the classification model, which represents the proportion of the number of accurately predicted classifications of the ostomy classification model to the total number of samples. Accuracy is simple and intuitive, easy to understand and explain. It provides a comprehensive evaluation of the overall performance of the model.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

Precision is a measure of how many of the samples that the model predicts to be positive are actually positive. Accuracy rate is very important for dealing with false positive cases (predicting a negative class error as a positive class). In some applications, such as medical diagnostics, we are more concerned with how many of the model's predictions are accurate positives.

$$precision = \frac{TP}{TP + FP}$$

Recall

Recall is a measure of a model's ability to correctly predict a positive sample. The recall rate is important for dealing with the problem of false negatives (predicting positive errors as negative). In some applications, such as disease detection, we are more concerned with whether the model can capture all the true positive classes as well as possible.

$$recall = \frac{TP}{TP + FN}$$

F1

F1 Score is an index that comprehensively considers accuracy rate and recall rate, and it is the harmonic average of accuracy rate and recall rate. F1 Score can comprehensively consider the accuracy and recall rate of the ostomy classification model, which can more accurately measure the performance of the model in the case of category imbalance.It can help us to find a balance between accuracy and recall.

$$F1 = \frac{2PR}{P + R} = \frac{2TP}{2TP + FP + FN}$$

Experimental Setup

This study was conducted in a computational environment powered by TensorFlow 2.9, Keras 2.12, and Python 3.11. The hardware infrastructure comprised of an Intel i5 CPU and an NVIDIA GTX1660 GPU, ensuring efficient processing and execution of our deep learning models. In our experimental design, we conducted a comparative analysis of the performance of two state-of-the-art deep learning architectures, namely ConvNeXt and MobileViT, in the context of a diagnostic task involving the categorization of irritant dermatitis, normal skin conditions, and other complications. This comparative study aimed to identify the model that delivers superior accuracy in the diagnosis of irritant dermatitis. Furthermore, we extended our comparison to the realm of optimization algorithms. We evaluated the effectiveness of two widely-used optimizers, Stochastic Gradient Descent (SGD) and Adam, in enhancing the learning process and improving the final performance of our models. Lastly, we embarked on an exploration of various learning rates, a critical hyperparameter in the training of deep learning models. This investigation aimed to understand the influence of different learning rates on the convergence speed and overall performance of our models. Through this, we hoped to identify an optimal learning rate that balances between fast convergence and model stability.

Ethical Considerations

The study adhered to the Declaration of Helsinki and was approved by the Ethics Committee of the Peking University (2024014). Written informed consent was waived due to the nature of the retrospective research design. The medical images utilized in the study did not typically contain personally identifiable information. Any images that did contain identifiable information, such as name tags, were cropped to ensure the privacy and confidentiality of the patients.

Results

As shown in Table 1, we trained both ConvNeXt and MobileViT models using different optimizers (SGD and Adam) and learning rates (0.01 and 0.001) to evaluate their effectiveness in diagnosing stoma complications. The highest accuracy (71.4%) was achieved by the ConvNeXt model with the Adam optimizer and a learning rate of 0.001, accompanied by a precision of 73.6%, recall of 67.1%, and F1-score of 70.2%. These results indicate that the ConvNeXt model offers relatively strong predictive power, particularly in identifying the positive category—irritant dermatitis. However, the recall score also highlights a remaining proportion of missed diagnoses, suggesting room for further refinement. The MobileViT model, although not outperforming ConvNeXt, still achieved reasonable diagnostic performance considering its lightweight architecture. The best performance was observed when trained with SGD and a learning rate of 0.001, yielding an accuracy of 64.4%, precision of 64.2%, recall of 57.8%, and F1-score of 60.8%.

To provide a more comprehensive evaluation, Figures 2 and 3 present the confusion matrices, ROC curves and AUC (Area Under Curve) scores for the best-performing ConvNeXt and MobileViT models, respectively. For the ConvNeXt model (Figure 2A), the model demonstrated strong classification performance for Normal (24 correctly identified out of 30) and Irritant Dermatitis (23 correctly identified out of 30). However, the model struggled with the Other Diseases category, correctly identifying only 16 out of 30 cases, with 8 misclassified as Normal and 6 as Irritant Dermatitis. This indicates a notable challenge in distinguishing Other Diseases from the other two categories. The MobileViT model (Figure 2B) showed a more balanced performance across all categories. While its classification of Normal cases was less accurate (only 14 correctly identified out of 30, with 10 misclassified as Irritant Dermatitis), it performed relatively well in detecting Irritant Dermatitis (22 correctly identified out of 30) and Other Diseases (21 correctly identified out of 30).

Table 1 Experimental Results for the ConvNeXt and MobileViT Models

Model	Opt	LR	Accuracy	Precision	Recall	F1
ConvNeXt	sgd	0.010	0.689	0.686	0.656	0.670
ConvNeXt	sgd	0.001	0.700	0.732	0.667	0.698
ConvNeXt	adam	0.001	0.714	0.736	0.671	0.702
ConvNeXt	sgd	0.010	0.622	0.629	0.622	0.626
ConvNeXt	sgd	0.001	0.633	0.667	0.578	0.619
MobileViT	adam	0.001	0.619	0.658	0.598	0.627
MobileViT	sgd	0.010	0.611	0.655	0.611	0.632
MobileViT	sgd	0.001	0.644	0.642	0.578	0.608

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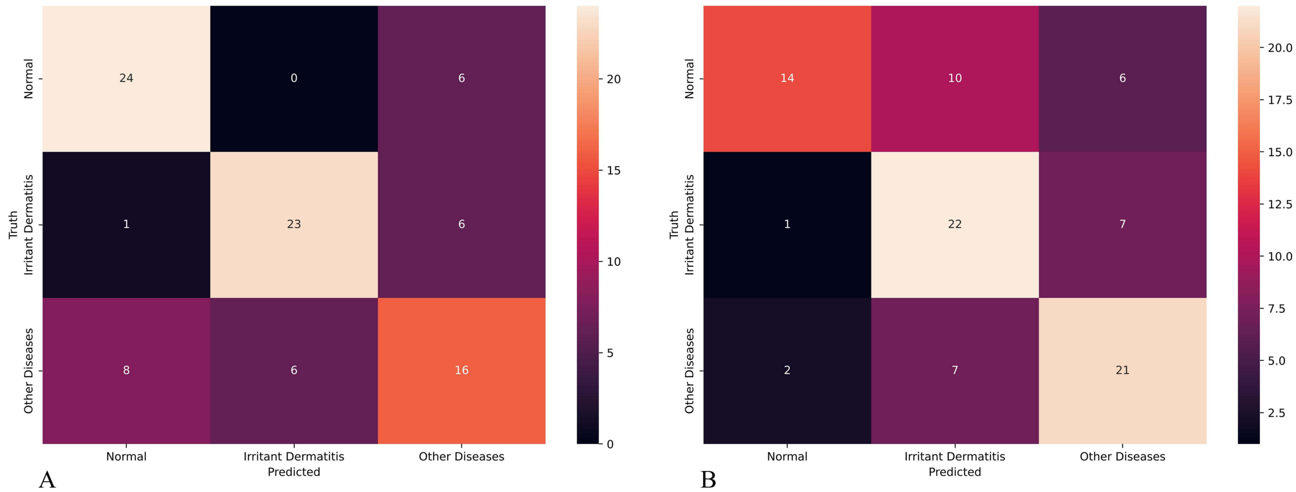

Figure 2 Confusion matrix. (**A**) Confusion matrix of the ConvNeXt model. (**B**) Confusion matrix of the MobileViT model.

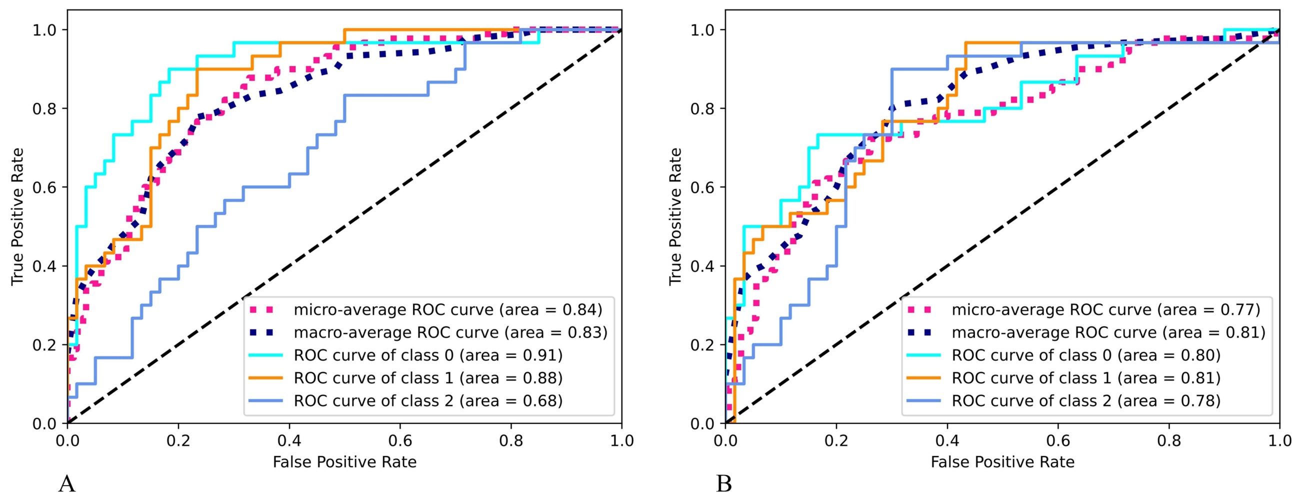

Figure 3 ROC curves of classification models. (**A**) ROC curves of the ConvNeXt model. (**B**) ROC curves of the MobileViT model.

The ConvNeXt model (Figure 3A) achieved a micro-average AUC of 0.84 and a macro-average AUC of 0.83, reflecting strong overall classification performance. In contrast, the MobileViT model (Figure 3B) showed a micro-average AUC of 0.77 and a macro-average AUC of 0.81, indicating slightly lower overall classification performance but more balanced prediction capability across categories.

Discussion

To the best of our knowledge, this study is the first to apply artificial intelligence technology to achieve diagnosis of irritant dermatitis in stoma patients. By comparing two advanced convolutional neural network models - ConvNeXt and MobileViT - for the intelligent diagnosis of enterostomal irritant dermatitis, this study aims to explore the optimal model suitable for the intelligent diagnosis of such skin lesions. Our experimental results show that the ConvNeXt model outperforms the MobileViT model in terms of accuracy, precision, recall, and F1 scores, and in particular exhibits the best overall performance using the Adam optimizer and 0.001 learning rate configuration. The reason for the superior performance of the ConvNeXt model in this study may be related to its ability to capture image features specific to enterostomal irritant dermatitis more effectively. The diagnosis of enterostomal irritant dermatitis usually relies on the microscopic features of the skin lesion, such as the color change of the inflamed area, the border definition, and the accompanying swelling or exudation.[24] ConvNeXt is able to efficiently extract these complex spatial features through its innovative convolutional structure, which improves the diagnostic performance of the model. In contrast, the MobileViT model, despite its lightweight advantage, may be limited in its feature extraction performance by the model structure.[25] MobileViT combines Transformer with convolutional networks aiming to capture global dependencies, but may be weaker than the ConvNeXt model when dealing with medical images with rich local texture information.

Further, upon deeper analysis of the confusion matrices and ROC curves of ConvNeXt and MobileViT, it is observed that ConvNeXt has a poorer recognition performance for "other complications", while MobileViT underperforms in recognizing "normal stoma". One possible explanation is that the "other complications" category encompasses a variety of ostomy diseases, each with its unique characteristics, which significantly increases the complexity of PSCs classification for the models. When ConvNeXt attempts to recognize "other complications", the diversity of the semantics often leads to misclassifications into "normal stoma" and 'Irritant Dermatitis', thereby enhancing the recall for "normal stoma" and 'Irritant Dermatitis' but adversely affecting their precision. Conversely, due to the semantic interference from different diseases within "other complications", MobileViT struggles to accurately recognize "normal stoma", often misclassifying it as 'Irritant Dermatitis' or "other complications", which results in a higher recall for 'Irritant Dermatitis' and "other complications" but compromises their precision.

Despite the promising performance of our model in automatically identifying normal, irritant dermatitis, and other complications, several limitations warrant further consideration. Firstly, our approach to data preprocessing, including data oversampling and enhancement, although beneficial for model robustness, may inadvertently encourage the model to learn repetitive features. This redundancy, resulting from the mere duplication of minority class samples, potentially exacerbates the risk of overfitting without genuinely enhancing the model's ability to generalize across varied lesion characteristics. Secondly, our reliance on the latest neural network architectures, such as ConvNeXt and Mobilevit, for superior feature extraction and pattern recognition does not fully mitigate the challenges posed by image-level supervision alone. Finally, although our experiments demonstrated the effectiveness of the model in classifying stoma complications, the dataset used for the experiments was relatively small, which limits further evaluation and optimization of the model performance. To ensure the effectiveness and utility of the model in clinical application scenarios, testing and validation on larger datasets are needed.

Implications for Future Research

Future studies could further explore the optimization and customization of the model, mainly including: (1) Data diversity and accessibility: to further improve the accuracy and generalization ability of the model, access to more diverse and representative datasets is required. This includes images of different types and stages of irritant dermatitis, as well as data from different populations (age, gender, skin color, etc); (2) Model interpretability: in the medical field, model interpretability is very important as it relates to the level of trust physicians have in the model's predictions. Although ConvNeXt has demonstrated superior performance, deep neural networks are often viewed as "black boxes" and it is difficult to explain their decision-making process. Future work should focus on improving the interpretability of the model, eg, by integrating visualization tools to enable physicians to understand how the model identifies specific skin lesions; (3) Clinical integration and utility testing: the final evaluation of the model is not only dependent on its performance in a laboratory setup, but it also needs to be validated in a real clinical setting. This includes assessing the utility of the model, its compatibility with existing medical processes, and its accuracy in real-world use. In addition, given the need for continuous monitoring of stoma patients, the model should be deployed to support mobile devices and remote access for both patients and physicians.

Conclusion

In summary, the ConvNeXt model was selected as the optimal model for this study due to its excellent performance, stable generalization ability, and effectiveness in processing images of irritant dermatitis in stoma patients. However, the challenges of data diversity, model interpretability, and clinical integration must still be addressed for the technique to better serve clinical applications. Future research should focus on optimizing the model structure, improving the interpretability of the model, and performing extensive clinical validation to achieve the practicality of intelligent diagnosis of irritant dermatitis in stoma patients.

Data Sharing Statement

The datasets used and/or analyzed during the current study are available from the corresponding author (ZWW) on reasonable request.

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Disclosure

The authors declare that they have no competing interests in this work.

References

1. Bray F, Laversanne M, Sung H, et al. Global cancer statistics 2022: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *Ca A Cancer J Clin*. 2024;74:229–263. doi:10.3322/caac.21834
2. Cervantes A, Adam R, Roselló S, et al. Metastatic colorectal cancer: ESMO clinical practice guideline for diagnosis, treatment and follow-up. *Ann Oncol*. 2023;34:10–32. doi:10.1016/j.annonc.2022.10.003
3. Pine J, Stevenson L, On J. Intestinal stomas. *Surgery*. 2023;41:55–61. doi:10.1016/j.mpsur.2022.10.010
4. Guerra E, Fc D, Di PC, et al. Peristomal skin complications: detailed analysis of a web-based survey and predictive risk factors. *Healthcare-Basel*. 2023;11:1823. doi:10.3390/healthcare11131823
5. Wei-Ying Z, Hui-Ren Z, Hai-Ping Y, et al. The effect of telemedicine on stoma-related complications in adults with enterostomy: a systematic review and meta-analysis. *INT WOUND J*. 2024;21:e14572. doi:10.1111/iwj.14572
6. D'Ambrosio F, Pappalardo C, Scardigno A, et al. Peristomal skin complications in ileostomy and colostomy patients: what we need to know from a public health perspective. *Int J Environ Res Public Health*. 2022;20:79. doi:10.3390/ijerph20010079
7. Cr R, Goldberg M, Jaszarowski K, et al. Peristomal skin health: a WOCN society consensus conference. *J Wound Ostomy Continence Nurs*. 2021;48:219–231. doi:10.1097/WON.0000000000000758
8. Rolls N, de Fries Jensen L, Mthombeni F, et al. Healthcare resource use and associated costs for patients with an ileostomy experiencing peristomal skin complications. *Int Wound J*. 2023;20:2540–2550. doi:10.1111/iwj.14118
9. John B, Kim M, Forgrave D. Risk factors associated with peristomal skin complications: integrative literature review. *J Nurs Educ Pract*. 2019;9:82. doi:10.5430/jnep.v9n7p82
10. Bhoyrul B, Ondhia D, Lyon C. Botulinum neurotoxin A is an effective treatment for irritant dermatitis caused by ostomy leaks in patients with retractile stomas. *Br J Dermatol*. 2019;181:629–631. doi:10.1111/bjd.17856
11. Gray M, Jc C, Doughty D, et al. Peristomal moisture-associated skin damage in adults with fecal ostomies: a comprehensive review and consensus. *J Wound Ostomy Continence Nurs*. 2013;40:389–399. doi:10.1097/WON.0b013e3182944340
12. Brady RRW, Scott J, Grieveson S, et al. Complications and healthcare costs associated with the first year following colostomy and ileostomy formation: a retrospective study. *J Wound Ostomy Cont Nurs*. 2023;50:475. doi:10.1097/WON.0000000000001028
13. Cross HH. CE: nursing care for patients after ostomy surgery. *Ame J Nurs*. 2023;123:34–41. doi:10.1097/01.NAJ.0000947460.38199.fe
14. Zhang X, Ma L, Sun D, et al. Artificial intelligence in telemedicine: a global perspective visualization analysis. *Telemed E-Health*. 2024;30:e1909–e1922. doi:10.1089/tmj.2023.0704
15. Suganyadevi S, Seethalakshmi V, Balasamy K. A review on deep learning in medical image analysis. *Int J Multimed Inf R*. 2022;11:19–38.
16. AlSadhan NA, Alamri SA, Ben Ismail MM, et al. Skin cancer recognition using unified deep convolutional neural networks. *Cancers*. 2024;16:1246. doi:10.3390/cancers16071246
17. Das SK, Roy P, Singh P, et al. Diabetic foot ulcer identification: a review. *Diagnostics*. 2023;13. doi:10.3390/diagnostics13121998
18. Seo S, Kang J, Ih E, et al. Visual classification of pressure injury stages for nurses: a deep learning model applying modern convolutional neural networks. *J Adv Nurs*. 2023;79:3047–3056. doi:10.1111/jan.15584
19. Andersen NK, Trøjgaard P, Herschend NO, et al. Automated assessment of peristomal skin discoloration and leakage area using artificial intelligence. *Front Artif Intell*. 2020;3:72. doi:10.3389/frai.2020.00072
20. Bai S, Hu S, Cui X, et al. A lightweight and efficient CNN based on VGG-16 variant for emotion recognition. 5th International Conference on Computer Information Science and Application Technology (CISAT 2022) 2022; 12451.
21. Liu Z, Mao H, Wu C, et al. A ConvNet for the 2020s. 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2022; 11966–11976.
22. Mehta S, Rastegari M. MobileViT: light-weight, general-purpose, and mobile-friendly vision transformer. *ArXiv*. 2021:abs/2110(02178).
23. Mehta S, Rastegari M. *MobileViT: Light-Weight, General-Purpose, and Mobile-Friendly Vision Transformer*. Ithaca: Cornell University Library; 2022. arXiv.org.
24. Bains SN, Nash P, Fonacier L. Irritant contact dermatitis. *Clin Rev Allerg Immu*. 2019;56:99–109. doi:10.1007/s12016-018-8713-0
25. Lee SI, Koo K, Lee JH, et al. Vision transformer models for mobile/edge devices: a survey. *Multimedia Syst*. 2024;30:109. doi:10.1007/s00530-024-01312-0