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Classification of human scabies skin disease using ConvNeXt

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Abstract

Scabies is a contagious skin disease caused by Sarcoptes scabiei and remains a health issue in many countries, including Indonesia. Clinical diagnosis is often difficult due to symptom similarities with other skin conditions. This study evaluates the ConvNeXt architecture for scabies classification from skin images to support automated diagnostic systems. The dataset consisted of 273 images (86 scabies and 187 non-scabies), expanded through cropping to 819 images, divided into 488 scabies and 331 non-scabies images. ConvNeXt was trained with fine-tuning at stage 3, implemented using PyTorch on an A100 GPU with the AdamW optimizer. Evaluation used 70:15:15, 80:10:10, and 5-Fold Cross Validation schemes with accuracy, precision, recall, and F1-score metrics. The best configuration (learning rate 0.0001, batch size 32) achieved 95.97% testing accuracy. Overall, ConvNeXt reached 97.75% average accuracy and an F1-score near 0.98, demonstrating highly competitive performance that slightly exceeds established baselines like ResNet-50 (97.69% accuracy). This shows its potential as an accurate and practical solution for automated scabies diagnosis in resource limited healthcare settings.

Key words: Automated Diagnosis, ConvNeXt, Deep Learning, Image Classification, Scabies.

INTRODUCTION

The skin represents the external bodily structure functioning as a safeguard against mechanical, chemical, and pathogenic threats, ultraviolet radiation, and dehydration [1]. Structurally, the skin is composed of the epidermis, dermis, and hypodermis, playing a critical role in physiological homeostasis [2]. High environmental exposure makes the skin vulnerable to various disorders, including the effects of pollution and radiation, which can trigger various skin diseases [3], [4]. One of the skin diseases commonly found globally and nationally is scabies. Scabies arises from an infestation of the skin caused by the mite known as sarcoptes scabiei var. Hominis, and it manifests with intense pruritus alongside a risk of developing subsequent bacterial infections [5], [6], [7]. Its prevalence rate exceeds 200 million cases annually [8], [9], [10]. In indonesia, scabies is a significant health issue in terms of its spread [11]. To address this, the condition is typically identified through physical examinations focusing on visible clinical signs. However, the symptoms it presents are frequently similar to those found in other skin conditions, which can lead to incorrect identification of the illness. Walton (2007) noted that because scabies symptoms frequently mimic other dermatological conditions, traditional diagnostic methods have an accuracy rate of less than 50% [12]. A similar finding was reported by lugović-mihić et al. (2022), who noted that some scabies cases were misdiagnosed as allergic conditions such as eczema or contact dermatitis [13]. Diagnostic precision can be improved through the use of supportive examinations like polymerase chain reaction (pcr), microscopy, and enzyme-linked immunosorbent assay (elisa) can enhance diagnostic accuracy, but these procedures require specialized facilities and medical personnel. Supporting examinations such as Microscopic examination, polymerase chain reaction (pcr), and enzyme-linked immunosorbent assay (elisa) can improve diagnostic accuracy, but these procedures require facilities and medical personnel that are not always available [14].

The swift advancement in computer vision has notably transformed how medical images are analyzed, moving from typical machine learning techniques to more advanced deep learning methods [15-18]. Distinct from standard techniques that depend on manually selecting features, deep learning frameworks present strong automated learning of features. Badri et al. (2023) emphasized this benefit by illustrating that CNN designs can pull out very distinctive features, reaching an impressive average precision of 99.99% in image sorting tasks without needing custom-built descriptors.

In the medical domain, the reliability of CNN-based models is well-documented. Anantama et al. (2022) addressed the challenge of class imbalance in pneumonia detection by applying Cost-Sensitive Convolutional Neural Networks. Their study proved that with proper loss function adjustments, the model could improve specificity while balancing sensitivity, which is crucial for reducing false negatives in unbalanced medical datasets.

Specific to the dermatological field, classifying skin lesions remains challenging due to high visual similarity. Riyana et al. (2024) successfully tackled this by optimizing the DenseNet201 architecture using random search. Their results showed a significant performance leap, boosting the model's accuracy from 63% (baseline) to 80% (optimized), demonstrating that hyperparameter tuning is essential for distinguishing subtle skin disease patterns. Closer to the specific subject of this study, Waldamichael et al. (2023) utilized ResNet-50 and ResNet-101 for scabies detection, achieving an average accuracy of 95% by combining clinical images with patient metadata.

Recent improvements in deep learning have led to more optimized architectures, building on the success of ResNet models in earlier studies. ConvNeXt is a convolutional neural network (CNN)-based architecture that simplifies the ResNet design while adopting techniques from vision transformers, such as large kernels, Layer Normalization, and hierarchical structures. This architecture has has shown exceptional effectiveness in different computer vision tasks, including classification and segmentation [19]. Recently, ConvNeXt has also demonstrated superior performance in various other medical imaging applications, such as malaria parasite detection [20], brain tumor grade classification [21], and the classification of dry and wet macular degeneration [22]. However, no studies have specifically evaluated the performance of ConvNeXt for medical image-based scabies classification. Therefore, this study attempts to take advantage of this opportunity. This study aims to evaluate ConvNeXt's performance in classifying scabies from skin images. ConvNeXt was chosen for this study over other modern architectures like DenseNet or Vision Transformer (ViT). The primary reason is its ability to perfectly balance the high-performance feature extraction of ViTs with the computational efficiency of CNNs, which is ideal for clinical setups. The results are expected to contribute significantly to the development of a fast, accurate, and applicable automated diagnosis system in healthcare facilities with limited resources.

MATERIAL AND METHODS

This research is divided into four main stages. The research methodology is described systematically through the diagram shown in Figure 1.

Data Collection

This study used a dataset of 273 images collected by the researcher. The images were taken using a smartphone device. The data was divided into two main classes, namely 86 images of scabies and 187 images of non-scabies. The non-scabies category includes several other types of skin diseases such as atopic dermatitis, contact dermatitis, numular dermatitis, diaper dermatitis, seborrheic dermatitis, pyoderma, prurigo, and healthy skin. Representative examples of images in the dataset can be seen in Figure 2.

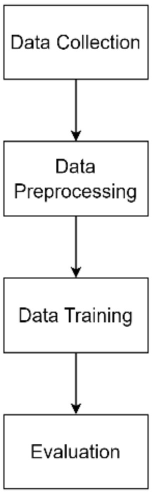

Fig. 1. Research flow

Fig. 1. Dataset sample

Data Preprocessing

Each image often contains more than one skin lesion, so manual cropping was performed to obtain a more specific lesion area in both scabies and non-scabies images. After manual cropping, the dataset reached a total of 819 images, comprising 488 images in the scabies category and 331 images in the non-scabies category. The non-scabies class includes both other skin diseases and healthy skin. Next, the cropped images were divided into three subsets using the data splitting method, namely training, validation, and testing data with two ratio schemes, namely 70:15:15 and 80:10:10. Data augmentation techniques were applied specifically only to the training set to enhance model generalization. The validation and testing sets remained in their original state to ensure an unbiased evaluation. In addition to static division, the K-Fold Cross Validation method was also used with a value of $k = 5$. The next steps included converting the images to RGB format, resizing them to 224×224 pixels, and normalizing the pixel values by dividing them by 255 to place them in the range [0,1]. After preprocessing, augmentation was performed with geometric transformations (+90° rotation, -90° rotation, horizontal and vertical flipping).

These specific geometric transformations were chosen because skin lesions do not possess a fixed or standard orientation. In real-world scenarios, images of scabies can be captured from various camera angles. Applying rotations and flipping allows the training dataset to simulate these diverse orientations. As a result, the model is forced to learn essential morphological features, including texture, shape, and color, instead of memorizing the spatial orientation of the lesions. Consequently, this approach prevents the model from overfitting to the specific alignments of the original images and significantly improves its generalization capability when encountering unseen data.

Data Training

The ConvNeXt architecture employed in this study is constructed from a series of residual blocks designed to optimize feature extraction efficiency. As illustrated in Figure 3, the fundamental ConvNeXt block adopts an inverted bottleneck structure similar to Transformers. It utilizes a large-kernel depthwise convolution (7 x 7) to capture broader spatial contexts, followed by an expansion layer (4 x dimensions) and a pointwise projection, stabilized by Layer Normalization and GELU activation. This design allows the model to learn complex patterns of scabies lesions effectively while maintaining computational efficiency.

To identify the optimal learning strategy, this study implemented and compared two training scenarios as depicted in Figure 4. The first scenario (Figure 4a) functions as a baseline using a feature extraction approach, where the entire backbone (Stage 1 to Stage 4) is frozen, and only the classifier head is trainable. The second scenario (Figure 4b) represents the proposed fine-tuning strategy, where the weights are unfrozen starting from Stage 3 to the final classifier. By unfreezing Stage 3 and

Stage 4, the model retains low-level generic features in the early layers while adapting high-level semantic features specifically for scabies classification. The training process was implemented using the PyTorch framework on a Google Colab Pro environment equipped with an A100 GPU.

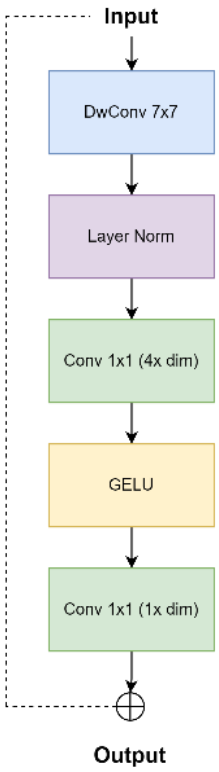

Fig. 3. ConvNeXt block details

To obtain the optimal configuration, hyperparameter tuning was performed on the learning rate (0.001, 0.0005, 0.0001) and batch size (16, 32, 64) using grid search with AdamW as the optimizer. The AdamW optimizer was chosen because it has been proven to provide faster and more stable convergence on the ConvNeXt architecture, especially in fine-tuning scenarios with diverse datasets and shifted distributions [23]. The combination of AdamW with techniques such as label smoothing has also been reported to improve the generalization of ConvNeXt models in malaria detection [20]. The training was conducted for 10 epochs, and model checkpointing was utilized to select the optimal weights based on the highest validation accuracy to prevent the use of an overfitted model

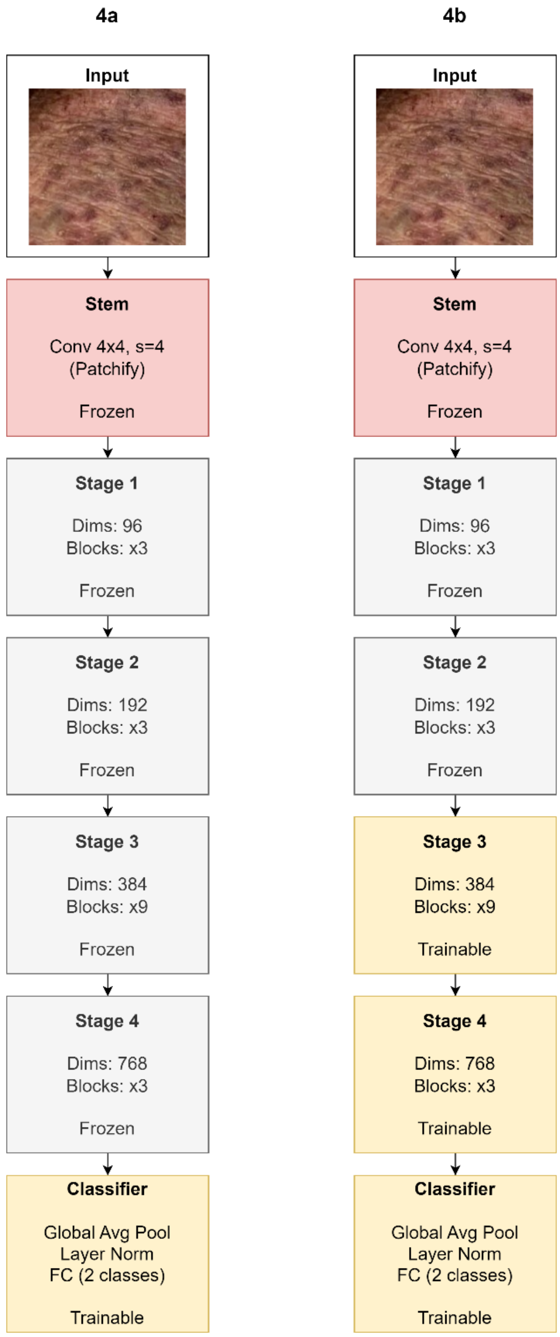

Fig. 4. Comparison of training strategies: (a) Feature extraction (frozen backbone) and (b) Fine-tuning (unfrozen from stage 3).

Evaluation

The tuning process was performed once on a 70:15:15 data split ratio scheme. The best results from the tuning process on this ratio were then used on all schemes. The model was tested on three data distribution schemes, namely 70% training : 15% validation : 15% testing, 80% training : 10% validation : 10%

testing, and 5-Fold Cross Validation (k = 5). In the 70:15:15 and 80:10:10 schemes, each model was trained 30 times to obtain the mean and standard deviation values. Meanwhile, in the K-Fold scheme, training was carried out 6 times. Performance evaluation used the metrics of accuracy, precision, recall, and F1-score.

RESULT AND DISCUSSION

The grid search process for hyperparameter tuning was performed on the convnext model, using a data split scheme of 70% training, 15% validation, and 15% testing. Tuning was performed on two main parameters, namely learning rate and batch size, with a total combination of 9 configurations. The grid search results are summarized in Table 1.

Table 1. Grid search hyperparameter results

No	Learning Rate	Batch Size	Validation Accuracy	Test accuracy
1	0.0001	32	97.56%	95.97%
2	0.0001	16	95.94%	94.35%
3	0.0001	64	95.12%	95.96%
4	0.0005	32	84.55%	89.52%
5	0.0005	64	78.04%	83.06%

The best results were obtained with a combination of a learning rate of 0.0001 and a batch size of 32, with a validation accuracy of 97.56% and a testing accuracy of 95.97%. This combination was then used consistently in all model testing on other data schemes, including the convnext model and the resnet-50 comparison model. The evaluation was carried out using accuracy, precision, recall, and f1-score metrics.

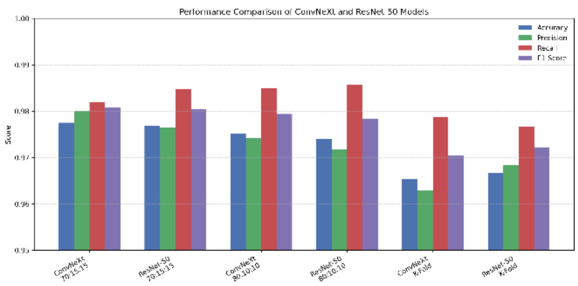

Fig. 5. Model performance comparison

Figure 5 shows a comparison of performance test results from nine CNN model training schemes, which are combinations of three model architectures and three data partitioning schemes. The ConvNeXt configuration with unfreeze up to stage 3 produced the best classification performance in most scenarios. It was decided to only unfreeze up to stage 3 because feature extraction is hierarchical. To find general, low-level features, the previously frozen stages are kept intact. On the other hand, unfreezing stage 3 and the classifier lets the model improve high-level, domain specific features, like the unique morphological patterns of scabies lesions. This targeted approach significantly reduces the likelihood of overfitting on a relatively small medical dataset. This model recorded an average accuracy of up to 97.75% in the 70:15:15 scheme, as well as consistently high precision, recall, and F1 scores.

Furthermore, an analysis of the different data splitting schemes revealed no significant performance disparity. The ConvNeXt (unfreeze) model achieved 97.75% accuracy using the 70:15:15 ratio and a closely comparable 97.52% using the 80:10:10 ratio, while the 5-Fold Cross Validation maintained a stable accuracy of 96.54%. This minimal variance demonstrates that the model is highly robust and its performance is not merely dependent on a specific dataset partition. This indicates that partially opening the feature extractor provides better adaptability to specific scabies data.

To further analyze the distribution of misclassifications, a confusion matrix is presented in Figure 6.

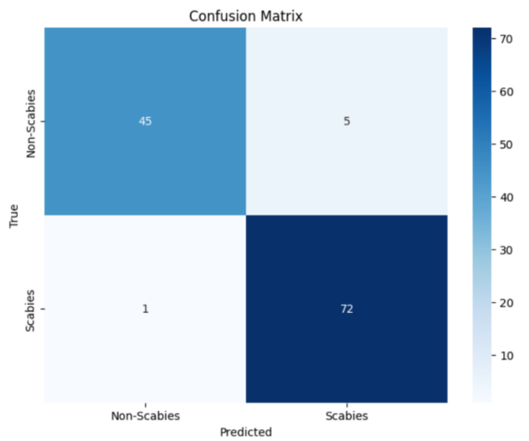

Fig. 6. ConvNeXt model confusion matrix

The matrix reveals the specific number of false positives and false negatives, providing deeper insight into the model's predictive behavior across the scabies and non-scabies classes. As shown in Figure 6, the model correctly identified 72 images of scabies, with only 1 images being misclassified as non-scabies.

Computational efficiency is an important aspect in model comparison. Efficiency is measured based on training time, inference time per image, and maximum memory usage during the training process. Figure 4 presents a graph comparing model efficiency.

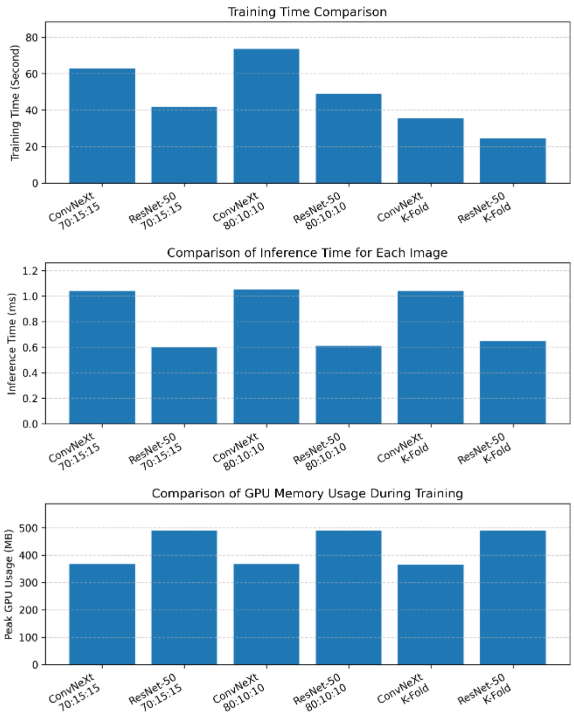

Fig. 7. Comparison model efficiency

Based on Figure 7, the ResNet-50 model shows the highest efficiency, with the fastest training time (24.3–49 seconds), low inference time (0.60–0.65 milliseconds per image), and relatively small GPU memory usage (489–490 MB). This efficiency is consistent with the characteristics of the ResNet architecture, where the use of residual blocks and small convolution kernels (3×3) results in lower computational complexity [24].

Conversely, ConvNeXt still provides a better balance between accuracy and efficiency. This is because ConvNeXt is an adaptation of modern CNN design with larger convolution kernels and simplified block structures. ConvNeXt is also capable of approaching the performance of Vision Transformer models while maintaining computational efficiency [19]. Model selection should be tailored to the needs of the application. In clinical scenarios with limited devices, ResNet-50 can be the primary choice due to its efficiency. However, for cases that require higher accuracy, ConvNeXt is more recommended as a balanced solution.

Furthermore, when compared to other recent deep learning studies in dermatology, the proposed model demonstrates superior performance. For instance, Riyana et al. (2024) employed the DenseNet201 architecture optimized with random search for skin rash classification, achieving an accuracy of 95.45%. In comparison, our ConvNeXt model reached a higher average accuracy of 97.75%. This indicates that while various modern architectures are effective, the ConvNeXt architecture with the proposed fine-tuning strategy offers better feature representation capabilities for detecting subtle scabies lesions [17].

Unlike that approach, this study emphasizes the use of ConvNeXt architecture, which performs automatic feature extraction during the training process. Thus, ConvNeXt is more practical and in line with developments in deep learning technology. Our research shows that the ConvNeXt (unfreeze) model is a better choice for limited hardware situations than legacy models like ResNet-50, which have faster inference speeds. In particular, it gets much better accuracy while using less GPU memory during training (367 MB) than ResNet-50 (489 MB). This makes it very useful for use in clinical settings where resources are limited. In the ConvNeXt scheme with a ratio of 70:15:15, the model achieved an accuracy of 97.75% with precision, recall, and F1-score each approaching 0.98. Although the performance was very good, there were still some classification errors. These errors generally occur in non-scabies images that are detected as scabies, mainly due to visual similarities between classes, suboptimal image quality, and manual cropping that can remove important information. This shows that improvements in data quality and preprocessing stages are needed to further improve model accuracy.

Using external images (Out-of-Distribution testing), a qualitative analysis was conducted to shed more light on these classification errors and the general behavior of the model, as shown in Figure 8. The model's ability to accurately classify scabies and non-scabies lesions is demonstrated by the success cases. The failure cases, however, draw attention to the difficulties that arise when the model is subjected to external data with various visual properties.

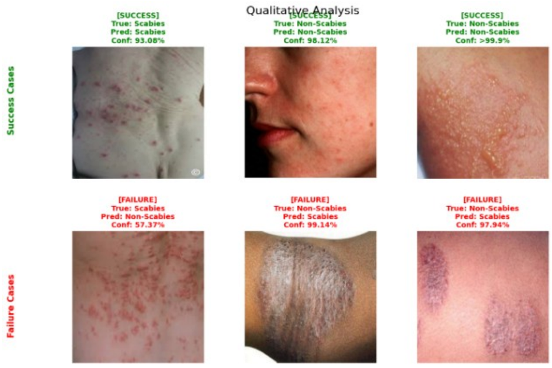

Fig. 8. Qualitative analysis of model predictions on external data

The phenomenon of model overconfidence is one of the intriguing findings of qualitative analysis. The ConvNeXt model often showed very high confidence scores (e.g., >99.9%), even in misclassified cases. In contemporary deep neural networks, this overconfidence is a well-documented behavior known as poor model calibration [25], in which the softmax probabilities do not fairly represent the actual likelihood of correctness. This behavior in the study's context is probably the result of the model overfitting to local textures in the comparatively small dataset. The model's raw confidence scores cannot be completely relied upon as an absolute measure of certainty in clinical settings, even though overall accuracy is still high at 97.75%. To make sure the model's output probabilities are more dependable for medical decision-making, future research should think about increasing the dataset variability or utilizing calibration techniques like temperature scaling. Regarding the potential generalizability of the model, while it demonstrated high accuracy on the current dataset, future evaluations should incorporate multi-center datasets encompassing various skin tones, lesion severities, and imaging devices to ensure the model remains robust and free from demographic bias across diverse clinical settings.

Overall, ConvNeXt demonstrated the best performance with high accuracy, precision, recall, and F1-score, and was able to maintain a balance between accuracy and computational efficiency compared to the comparison models. These findings confirm the potential of ConvNeXt as a reliable architecture to support automatic diagnosis systems based on medical images.

CONCLUSION

The results show that convnext is an effective architecture for detecting scabies skin disease, with a fine-tuning configuration unfreeze up to stage 3. This model achieved an average accuracy of 97.75%, an f1-score close to 0.98, and a recall of up to 0.98 in a testing scenario with a ratio of 70:15:15. Although convnext does not show superiority in terms of training and inference speed compared to resnet-50, this model has fewer parameters and shows good generalization capabilities without requiring augmentation of the validation and test data. Thus, convnext has the potential to be used as an efficient and accurate alternative architecture for medical image-based automatic diagnosis systems, particularly in the classification of scabies skin disease.

However, this study is limited by its relatively small dataset and potential data collection bias. Future research should focus on expanding the dataset to include more diverse skin types and lesion stages. Additionally, exploring newer architectures like Vision Transformers (ViT) could further enhance performance. Integrating clinical metadata, such as age and infection duration, could also provide a more reliable diagnostic tool for healthcare providers.

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