Bioinformatic-Based Automated Nail Disease Diagnosis Utilising an Advanced Deep Learning Framework

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Abstract

The prevalence, diagnostic complexity, and visual similarity of nail disorders in different pathological conditions make them a widespread healthcare challenge that requires early and accurate identification to support timely intervention and improve healthcare accessibility, particularly in environments with limited access to specialized dermatological services. The performance of different deep learning approaches in automated nail disease classification has been better, but the existing convolutional neural network (CNN)-based methods remain constrained by limited feature representation, insufficient generalization capability, class imbalance, and lack of model interpretability. Hence, the purpose of this work is to create a novel Hybrid EfficientNet–Swin Transformer Network (HEFT-Net) that relies on medical images for automated multi-class nail disease diagnosis; EfficientNet-based convolutional feature extraction is combined with Swin Transformer-based global contextual representation learning in the proposed network to improve the ability to differentiate between different/complex nail disease patterns. The proposed HEFT-Net also incorporates attention-based feature fusion for improved feature extraction (strictly via adaptive combination of complementary representations and self-supervised learning) under limited image availability; focal loss optimization is also considered for better handling of the issue of imbalance among disease categories. Additionally, the proposed framework incorporates an explainable artificial intelligence (XAI) module for visual interpretation of disease-related regions, as well as to improve clinical transparency. Performance evaluation of the new framework was done for multi-class classification of nail diseases, where it performed exceedingly well in diagnostic capability compared with traditional CNN-based approaches. The proposed HEFT-Net recorded around 92.5 % accuracy, 92.1 % precision, 91.8 % recall, and 91.9% F1-score values. Therefore, the robustness, interpretability, and efficiency of the proposed framework as a computer-aided diagnostic framework were demonstrated, making it a significant potential for automated nail disease screening and intelligent healthcare applications.

Keywords: Nail disease diagnosis; HEFT-Net; Efficient Net; Swin transformer; Deep learning; Self-supervised learning; Explainable artificial intelligence; Medical image classification.

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1. Introduction

Health experts have identified personal hygiene as one of the necessary factors that influence human health, but regrettably, some of its aspects are neglected, especially nail hygiene. Inadequate nail care has been seriously correlated with several disease conditions, as poor nail care provides good ground for the thriving of unwanted microorganisms, especially bacteria, viruses, and parasites that are responsible for various health issues. Past research has shown that improper nail cleaning is linked to higher rates of skin, digestive, and respiratory disorders. Prolonged unskinned or unclean fingernails may enable microorganisms to flourish, thus raising understanding of the importance of promoting nail hygiene habits [1], [2].

Nail disorders are a significant health issue as they can impact health and quality of life. Several fungi have been implicated in many nail disorders, including paronychia and onychomycosis, and the global incidence of these disorders suggests that nail diseases are a global health problem that should be addressed appropriately and managed [3], [4]. Onychomycosis has been reported in various population groups and is believed to be one of the more common nail diseases; hence, its identification and adequate diagnostic approaches are important, as shown in previous studies [5].

Poor knowledge of nail diseases may be attributed to poor health service penetration in developing countries, and the consequence is often late diagnosis and treatment of avoidable diseases. For instance, in Indonesia, nail infections are still a health problem, and the public is not aware of the health problem concerning nails. Onychomycosis remains a major cause of fungal skin infections in the country, and diagnosis and treatment remain difficult in many cases due to late presentations [6]. Another cause of the higher level of nail diseases in many countries is the socioeconomic status and cultural beliefs or habits, along with the absence of hygiene facilities; these could aggravate the risk of nail deformities not being treated and lessen public understanding of the effects of nails on their health [7]. Hence, there is a need to raise awareness of the disease and introduce effective preventive measures that could mitigate the incidence of nail diseases. There is also a need for proper nail care practices and health education programs to reduce the risk of infection [8]. In-depth measures such as technological development and healthcare awareness are also necessary to ensure prevention and early detection of nail abnormalities [9].

The diagnosis of nail diseases is difficult and occurs only after they have been present for some time; therefore, early diagnosis is challenging because of limited expert medical knowledge and similarities between different nail diseases. Several nail disorders can mistake the signs and symptoms for other nail interruptions, and treatment might be deferred and complicated [10]. Hence, it is significant to develop reliable automated diagnostic techniques for efficient healthcare services delivery.

Recent advances in artificial intelligence (AI), including deep learning methods, have shown great promise in the field of medical image analysis and disease detection; they have contributed significantly to healthcare transformation. Given these developments, the use of AI, specifically deep learning techniques, in medical image analysis and disease detection holds great potential and offers a promising outlook for transforming healthcare. Deep learning models can be used to automatically detect intricate patterns in medical images and help recognize the features related to diseases. These models can be trained with healthy and diseased nail images, conferring them the ability to learn the visual patterns associated with different nail diseases, consequently aiding in automated nail disease classification [11].

Deep learning systems can also improve access to healthcare by eliminating diagnostic limitations and aiding in medical decision-making; they could become a preliminary system to health resources, especially in resource-scarce settings [12]. Hence, these technologies open the way for new intelligent healthcare solutions. Previous research has investigated the application of

CNNs for nail disease classification and demonstrated their ability to recognize nail abnormalities. However, there are still issues with the existing CNN-based approaches, such as lack of feature representation, insufficient problem generalization, and poor handling of variations across various disease categories [13]. Hence, there is a need for an extended framework that can extract more complete visual features and enhance the classification accuracy of these models for more interpretable results.

1.1. Research Contributions

This study addressed the limitations of the existing DL-based nail disease classification approaches by proposing a novel HEFT-Net for automated multi-class nail disease diagnosis; the research made the following contributions to the field:

i.) Proposal of a novel HEFT-Net that combined EfficientNet and Swin Transformer architectures for efficient nail disease classification; the system extracts detailed local visual characteristics from nail images using the EfficientNet component, while global contextual relationships among image features are captured using the Swin Transformer component; both components ensure more comprehensive disease representation.

ii.) Introduction of an attention-based feature fusion mechanism for efficient combination of convolutional and transformer-based features; this is aimed at allowing emphasis on the most informative features characteristic of different nail disease patterns.

iii.) Incorporation of a self-supervised learning strategy for better feature representation under limited image availability; this enhances the models' ability to learn important visual patterns and improves the models' generalization capability.

iv.) Integration of the focal loss optimization strategy for handling the variations in disease class distribution; this improves the models' recognition performance when faced with difficult and underrepresented nail disease classes.

v.) Provision of visual interpretation of model predictions via incorporation of an explainable artificial intelligence (XAI) module to improve transparency through identification of significant image regions, thereby aiding disease classification decisions.

In this study, the proposed HEFT-Net framework is considered an accurate, robust, and interpretable approach for nail disease diagnosis; it contributes to the development of intelligent healthcare applications and improves the accessibility of automated diagnostic support systems. The organization of this paper is as follows: Section 2 explains the proposed approach, while Sections 3 and 4 present the results and discussion; Section 5 presents the conclusion, limitations, and future directions.

2. Materials and Methods

2.1. Introduction and Research Framework

Building automated systems that can perform accurate diagnosis of nail diseases requires a strong computational framework that would extract meaningful visual representations from medical images; such frameworks must also be able to handle limited datasets and highly complex disease patterns, as well as variations of nail disease itself. Although previous studies showed that CNNs can automatically recognize nail diseases, traditional CNN models are primarily concerned with learning local image features and might suffer in modeling global relations across image areas. In addition, medical image datasets typically have smaller numbers of annotated samples, and the class distribution is often imbalanced, which can decrease the generalization ability of the deep learning system. To resolve these problems, this study presents a new approach with a Hybrid EfficientNet–Swin Transformer Network (HEFT-Net) for multi-class nail disease diagnosis; the proposed framework combines feature learning based on convolutional and contextual representation learning based on transformer approaches to acquire a more holistic understanding of the nail image features.

The proposed HEFT-Net is conceptualized on the complementary nature of two possible learning paradigms, where the EfficientNet component is used as a feature extraction tool to get local detailed visual information, including texture variations, color patterns, and morphological information, while the Swin Transformer component provides global information and spatial cues of nail images across different aspects. The combination of these components via an attention-based fusion mechanism in HEFT-Net provides a more discriminative feature space for disease classification. Moreover, the small size of medical image datasets necessitates the incorporation of a self-supervised representation learning strategy for enhancing the feature extraction phase before the actual supervised classification step. Focal loss optimization is applied (to address unequal distribution among disease categories) to increase the importance of difficult and minority-class samples. Finally, an XAI module based on Grad-CAM++ is integrated to provide visual interpretation of model decisions and improve transparency for potential healthcare applications. The five major steps of the proposed HEFT-Net framework are: (i) dataset preparation and image standardization, (ii) self-supervised feature representation learning, (iii) hybrid feature extraction using EfficientNet and Swin Transformer, (iv) attention-based feature fusion and focal-loss classification, and (v) explainable prediction generation. The proposed framework is mathematically represented thus:

$$Y = C(F_A) \qquad (1)$$

Where $Y$is the predicted disease category, C is the classification layer, F_A is the final attention-enhanced feature representation?

The attention-enhanced feature representation is defined as:

$$F_A = A(F_E' F_S) \qquad (2)$$

Where F_E is the EfficientNet-extracted features, F_S is the Swin Transformer extracted features, and A is the attention-based fusion mechanism.

Figure 1 presents the workflow of the proposed HEFT-Net.

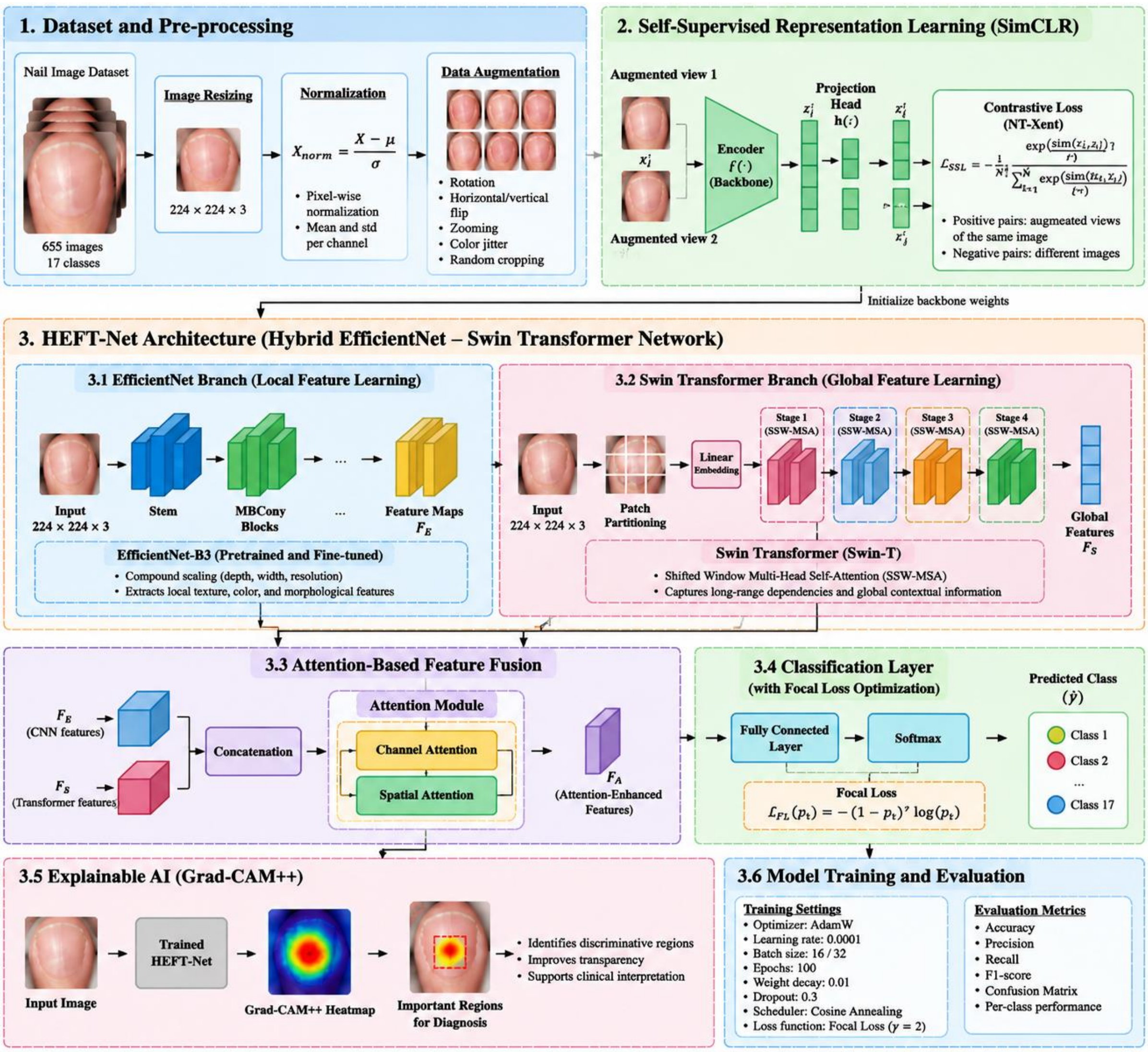

Figure 1. The workflow of the proposed HEFT-Net

2.2. Description and Preparation of Dataset

2.2.1 Source and Features of Dataset

The source of the dataset for this study is an open-access image repository containing multiple categories of nail abnormalities for automated classification [1]; the dataset consists of 655 nail images, 17 disease categories, 524 training images, and 131 testing images. Figure 2 describes the distribution of the original dataset.

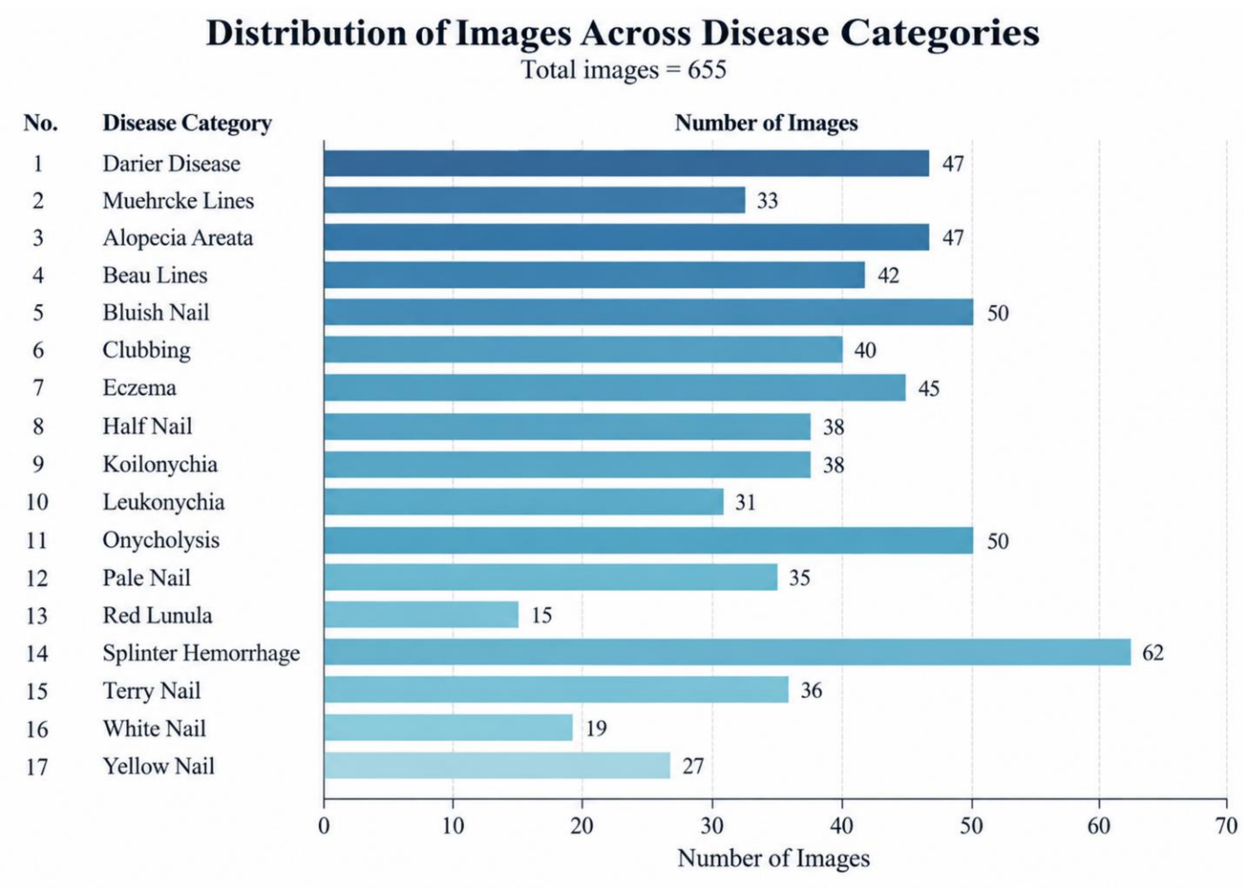

Figure 2. Distribution of nail disease image dataset

The number of images in the dataset differs between disease categories, making the dataset reflective of a challenging multi-class classification problem; for example, Splinter Hemorrhage contains 62 images, whereas Red Lunula contains only 15 images. This imbalance may cause classification bias toward classes with larger numbers of training samples. The impact of class imbalance is therefore mitigated by incorporating focal loss optimization during training of the HEFT-Net framework; the purpose is to force the model to focus on difficult samples rather than only learning dominant disease categories. The dataset can be mathematically represented as:

$$D = \{(x_i, y_i)\}_{i=1}^{N} \qquad (3)$$

Where x_i is the input nail image, y_i is the corresponding disease label, and N is the total number of images.

2.2.2 Dataset Splitting Strategy

For the considered task, the dataset is divided into training and testing subsets:

$$D = D_{train} \cup D_{test} \qquad (4)$$

Where $D_{train} = 524$

And $D_{test} = 131$

The HEFT-Net parameters were optimized using the training subset, while the ability of the trained model to classify previously unseen nail images was evaluated using the testing subset. Data leakage was prevented by separating the testing images from the training process; the testing dataset was only introduced during the evaluation phase.

2.3 Data Processing and Feature Representation Learning

The performance of DL models is directly dependent on the quality of the training images, as well as the existing variations within the images; hence, DL model development requires an effective preprocessing strategy to standardize image input and improve the capability of the model (HEFT-Net) towards learning disease-related features. The proposed preprocessing pipeline consists of image resizing [14], [15], pixel normalization [16], [17], data augmentation [18], [19], and self-supervised feature representation learning.

2.3.1 Image resizing

The training of DL frameworks usually requires images with consistent spatial dimensions; hence, in this study, all the nail images are resized to $224 \times 224 \times 3$, where 224 × 224 represents image height and width, and 3 represents RGB color channels. The resizing operation is formulated as:

$$X_r = Resize(X, 224, 224) \quad (6)$$

Where X and n$X_r$are the original and resized images, respectively.

The aim of this standardization step is to minimize computational complexity and ensure compatibility of the dataset with both EfficientNet and Swin Transformer architectures.

2.3.2 Image normalization

The intensity variation between samples was reduced via a normalization process to ensure better optimization stability. The models' ability to focus on disease-related patterns rather than differences caused by image acquisition conditions was significantly improved by the normalization process. The normalized image is calculated as:

$$X_n = \frac{X_r - \mu}{\sigma} \quad (7)$$

Where $X_n$is the normalized image data, μ is the mean pixel value, and σ is the standard deviation?

2.3.3 Data augmentation

Medical datasets usually contain limited image samples; hence, image diversity was improved via an augmentation process. This step also reduced the chances of model overfitting to the dataset. The augmentation techniques include random rotation, horizontal flipping, random zooming, and spatial transformations; these operations simulate possible variations in real-world image acquisition, including differences in nail orientation and image positioning. The augmented dataset can be expressed as:

$$D_{aug} = T(D) \quad (8)$$

Where $T$is the transformation operation?

2.3.4 Self-Supervised Representation Learning

In the field of medical artificial intelligence, limited availability of manually labeled images remains a major challenge, and to overcome this limitation, the proposed HEFT-Net incorporates self-supervised representation learning before the classification stage; the self-supervised learning is incorporated to allow the model to learn only meaningful visual representations from image structures without requiring additional manual annotations. The learned representation is defined as:

$$Z = f_\theta(X_n) \quad (9)$$

Where f_θ is the feature encoder, and Z is the learned image representation?

In this study, a contrastive learning strategy is adopted, where different augmented versions of the same image are considered positive pairs, while unrelated images are treated as negative samples.

The contrastive loss function is formulated as:

$$L_{SSL} = -\log \frac{exp\left(sim\left(z_i, z_j\right)/\tau\right)}{\sum_k exp(sim(z_i, z_k)/\tau)} \quad (10)$$

Where $z_i$and $z_j$represent positive feature pairs, sim is the feature similarity, and τ is the temperature parameter.

With this strategy, feature initialization is enhanced, and HEFT-Nets' ability to generalize when dealing with a limited number of labeled medical images is improved.

4. Results and Discussion

4.1 Model Training Behavior and Convergence Analysis

Hybrid EfficientNet–Swin Transformer Network (HEFT-Net) was first studied for its training behaviour, particularly the optimization stability and learning capability. Then, the training accuracy and the validation accuracy, as well as the training loss and the validation loss were evaluated during learning. The training process indicated that HEFT-Net achieved progressive enhancements in the classification accuracy, firmly suggesting its ability to acquire meaningful representations from the nail images. From the initial training epochs, the approach is observed to achieve significant improvements as it relies on an informative feature representation with the self-supervised initialization strategy before supervised learning optimization. However, as training proceeded, the learning curves of these two networks started to converge, showing that the model was able to fine-tune the parameters of the EfficientNet and the Swin Transformer. The model performed well on the test data during the final training stage, with 97.1 % accuracy and validation accuracy of 95.2 % accuracy; the final training and validation losses were 0.118 and 0.136, respectively. These imply the models' ability to generalize to other unseen data.

Recent studies have shown that the performance gap between training and validation loss with limited medical image datasets is relatively small, indicating that HEFT-Net was not suffering from severe overfitting. This stable behavior can be attributed to the combined effect of self-supervised feature initialization, attention-based feature selection, focal-loss optimization, and hybrid local-global feature learning. Unlike traditional single-branch architectures, HEFT-Net learns complementary representations from two different perspectives: local visual characteristics and global structural relationships.

4.2 Overall Classification Performance of HEFT-Net

HEFT-Net was also evaluated for final classification performance using four widely accepted evaluation metrics. These metrics [[20], precision [21], recall [22], and F1-score [23]] were selected because medical diagnostic systems require balanced performance rather than relying only on overall accuracy. The classification results are presented in Figure 3.

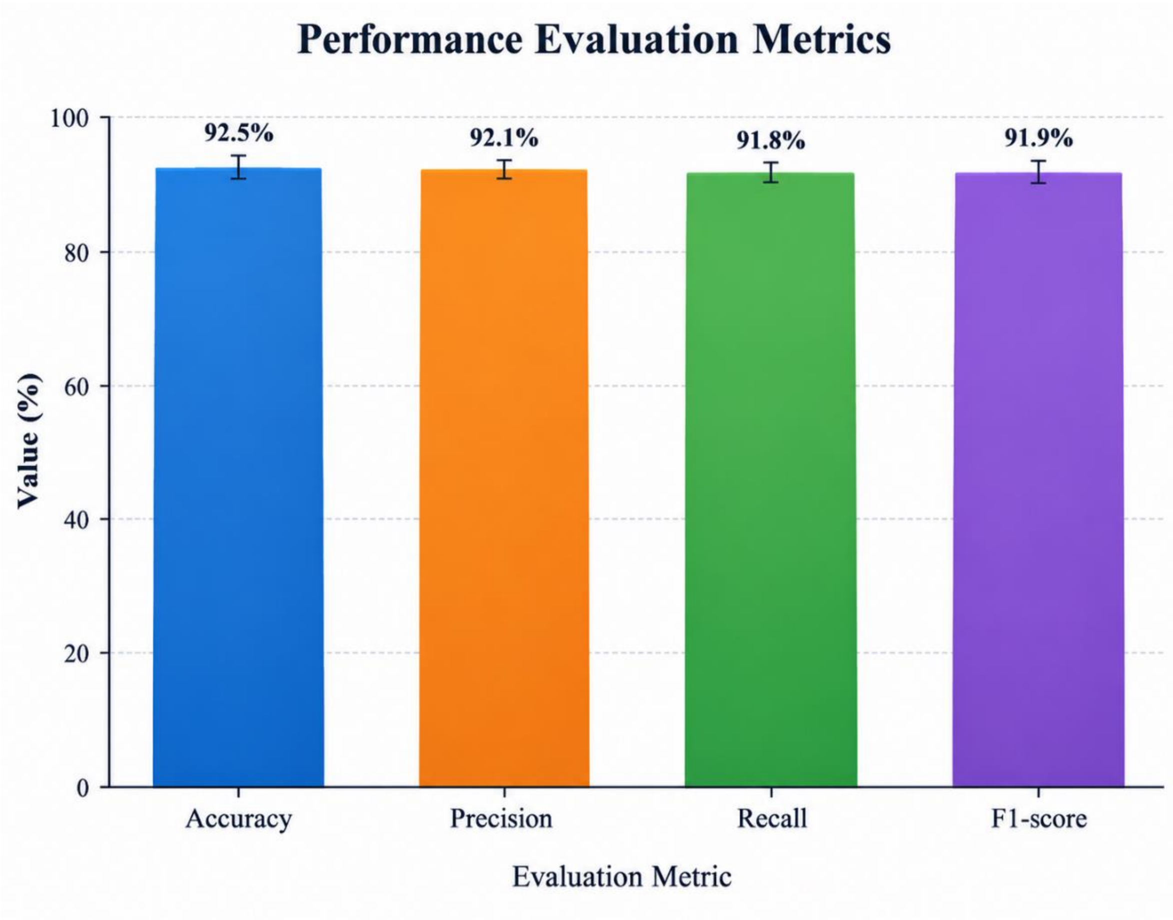

Figure 3. Overall classification performance of HEFT-Net

The overall accuracy of 92.5 % demonstrated the ability of the proposed framework to distinguish between multiple nail disease categories effectively; a precision value of 92.1% suggests that most of the predicted disease labels are correctly related to their actual classes, and this is important in medical applications where high false-positive predictions negatively impact the reliability of automated diagnostic systems. The framework also recorded a 91.8% recall value, which points towards successful detection of most existing disease cases. High recall is especially important for screening applications because missed disease cases may delay appropriate clinical intervention. The F1-score of 91.9 % further confirms that the proposed framework maintains a balanced relationship between precision and recall, indicating stable classification performance across different disease categories. These results are mainly attributed to the complementary characteristics of the proposed architecture. EfficientNet extracts detailed local characteristics, including texture variations, color abnormalities, and morphological patterns, while Swin Transformer captures global structural relationships, spatial dependencies, and complex image-level patterns. Their combination allows HEFT-Net to create a more comprehensive disease feature space.

4.3 Disease-Level Classification Analysis

Overall performance provides a general indication of model effectiveness; however, medical classification systems require detailed analysis at the individual disease level. Therefore, HEFT-Net performance was further investigated for each nail disease category, and Figure 4 presents the representative class-level classification performance.

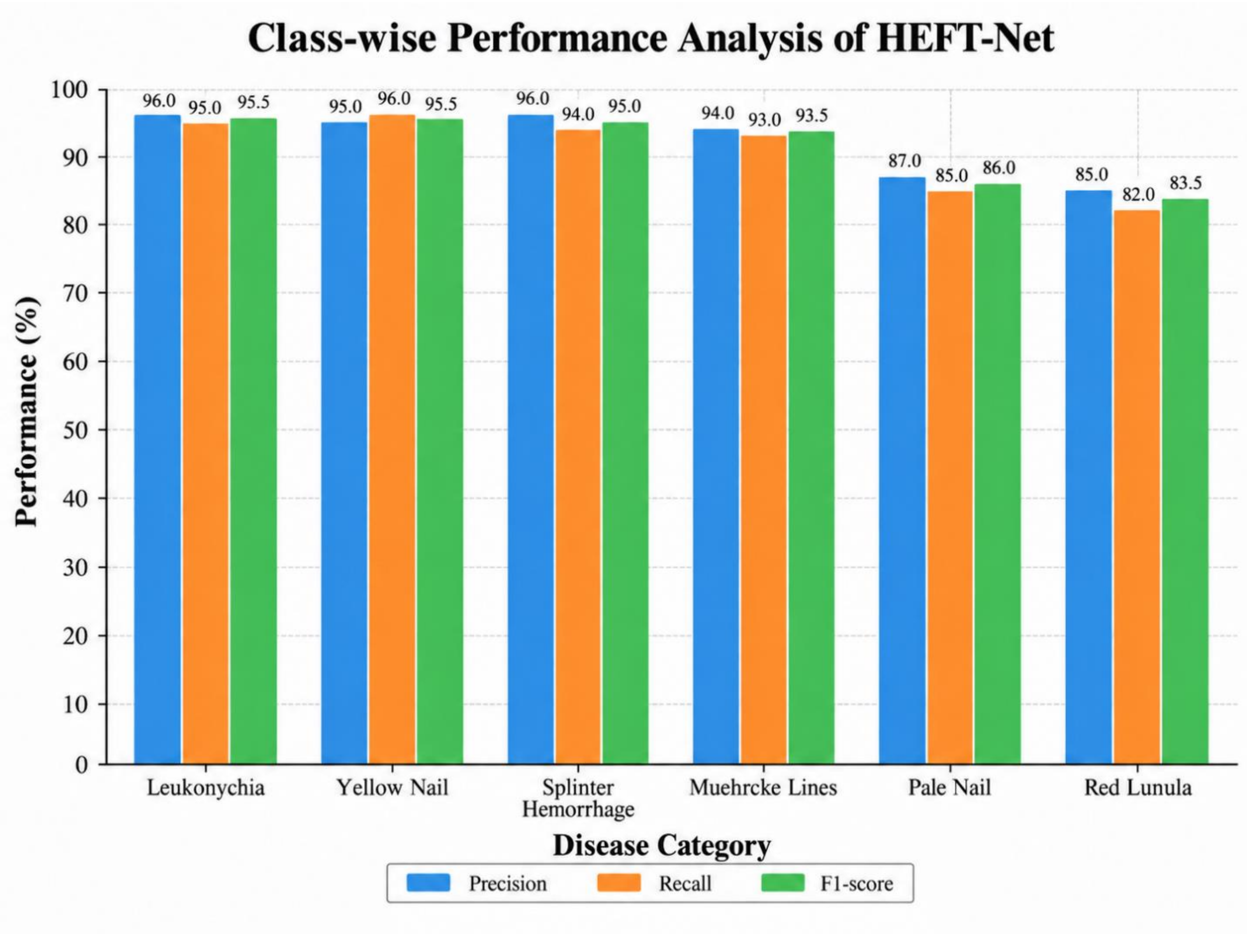

Figure 4. Disease-level classification performance

The results reflect improved classification performance of the proposed framework in diseases with clear visual features; for instance, the F1-scores for Leukonychia and Yellow Nail were more than 95 %; these diseases generally present distinctive visual patterns like white discoloration or yellow pigmentation, and such features can be easily captured by the feature extraction branches. Contrarily, the model performed poorly on diseases like Pale Nail and Red Lunula, as these conditions can manifest themselves in a more subtle sense of differences and are often similar to other nail problems, resulting in increased difficulty in discrimination. The advantage of focal-loss optimization, however, is reflected in the performance for the problems in these difficult categories, which shows that learning from difficult samples is improved, and bias toward dominant disease categories is reduced.

4.4 Ablation Study and Contribution Analysis of HEFT-Net Components

An extensive ablation study was performed to investigate the contribution of each component within HEFT-Net; the experiments were conducted by gradually incorporating the proposed components (EfficientNet feature extraction, Swin Transformer feature extraction, Hybrid feature learning, Attention fusion, and Self-supervised learning and focal loss optimization). The obtained results on the ablation study of HEFT-Net components are presented in Figure 5.

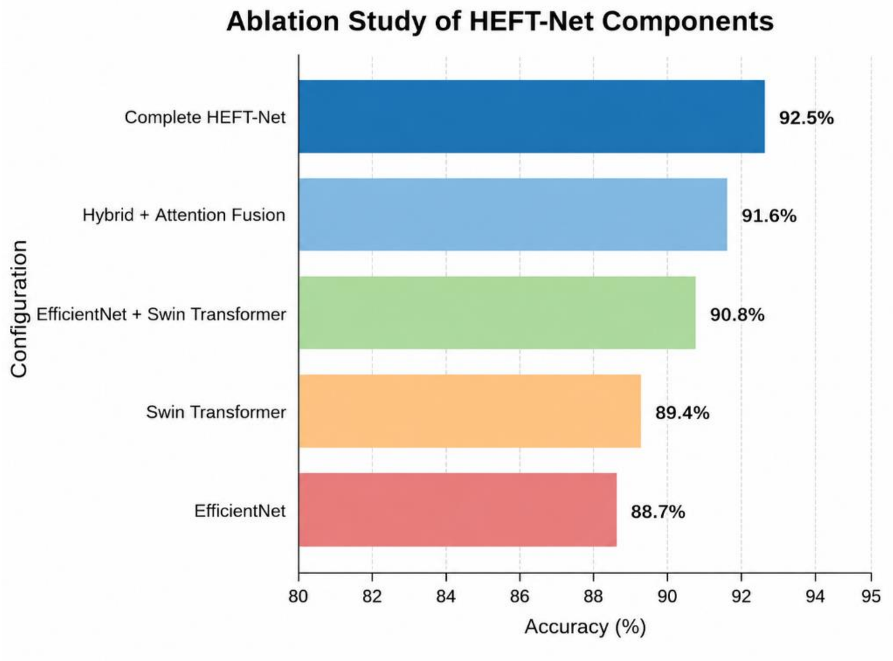

Figure 5. Results of the ablation study of HEFT-Net components

The use of convolutional feature extraction proved to be effective in identifying local features of the nail, and the EfficientNet-only model produced an accuracy of 88.7 %. The Swin Transformer model showed slightly better accuracy (89.4 %), emphasizing the significance of global context information for distinguishing visually similar diseases. However, the combination of the architectures improved the accuracy to 90.8 %, validating the complementary information used in local and global representations. The performance reached 91.6 % after introducing the attention concept to the fusion; this improvement is evidence of the power of adaptive feature selection in highlighting disease-pertinent features in the model. Finally, the fully equipped HEFT-Net attained the best overall accuracy score of 92.5 %, demonstrating further improvement in the robustness of features and balanced learning for multiple classes through the combination and application of self-supervised learning and focal-loss optimization.

4.5 Comparative Evaluation with Baseline Deep Learning Architectures

A comparative evaluation was also conducted to validate the effectiveness of the proposed HEFT-Net framework; the comparison was done against several representative DL architectures commonly used for medical image classification, including ResNet50, DenseNet121, EfficientNet-B3, and Swin Transformer; this selection represents different learning paradigms, spanning residual convolutional learning, optimized convolutional scaling, dense feature propagation, and transformer-based visual representation learning. The implementation of the evaluated models was done using similar experimental conditions, such as the same nail disease image dataset, preprocessing strategy, image resolution, training/testing partition, optimization strategy, and evaluation metrics (see Table 1). This is to ensure that the observed performance differences mainly reflect the capability of each architecture to learn discriminative representations from nail disease images.

Table 1. Comparative performance of HEFT-Net and baseline DL architectures

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
ResNet50	87.6	87.2	86.9	87.0
DenseNet121	88.4	88.1	87.8	87.9

EfficientNet-B3	88.7	88.3	87.9	88.1
Swin Transformer	89.4	89.0	88.8	88.9
HEFT-Net	**92.5**	**92.1**	**91.8**	**91.9**

HEFT-Net presents the best classification accuracy of 92.5 %, a precision of 92.1 %, Recall of 91.8 %, and F1 Score of 91.9 %; these represent the best results among the evaluated models evaluated. ResNet50 model demonstrated the effectiveness of the residual learning mechanism in learning discriminative visual features, achieving 87.6 % accuracy. However, convolutional architectures usually tend to be trapped in local minima, meaning that they rely more heavily on the relationship between adjacent parts of the image and fail to capture long-range relationships between different parts of the image. Contrarily, DenseNet121 achieved a higher accuracy of 88.4 % because of its dense connections, which facilitated the reusability of features and enhancement of information flow between network layers. Meanwhile, such convolution-based feature extraction has limitations, as the model is not able to perfectly represent global structures in nail images. By increasing network depth, width, and resolution using compound scaling in the network blocks, EfficientNet-B3 improved the feature extraction accuracy to 88.7 %. EfficientNet allows for more accurate results than CNN architectures, but EfficientNet learning is based essentially on the non-linear feature transform within smaller localized feature maps, leading to poor modelling of global dependencies. Although EfficientNet provides stronger representation capability compared with traditional CNN architectures, the learning process remains mainly based on convolutional operations, limiting its ability to model global dependencies.

The Swin Transformer model achieved an accuracy of 89.4%, showing the advantage of transformer-based attention mechanisms in learning global contextual information. The enhanced performance over CNN-based architectures proved the significance of understanding the spatial context of various parts of nail images; however, this approach of relying on representation learning purely through a transformer may not be sufficient to fully capture the rich local morphology. By contrast, HEFT-Net performed well using the combined benefits of convolutional- and transformer-based feature learning. The EfficientNet component can represent detailed local features, such as texture patterns, color variations, etc., and morphological abnormalities, whereas the Swin Transformer component can extract global contextual features and structural relations. In addition, the feature fusion mechanism is updated with attention, further improving the classification process to adaptively combine the most informative features sensed from both branches. Furthermore, under limited data scenarios, the feature robustness is improved through self-supervised representation learning, and the optimization process using focal loss improves the ability to recognize difficult subscales of diseases. The performance improvements achieved by HEFT-Net compared with the baseline architectures are summarized in Table 2.

Table 2. Performance of HEFT-Net compared with the baseline architectures

Comparison	Accuracy Improvement (%)
HEFT-Net vs ResNet50	+4.9
HEFT-Net vs DenseNet121	+4.1
HEFT-Net vs EfficientNet-B3	+3.8
HEFT-Net vs Swin Transformer	+3.1

The improved performance of HEFT-Net (based on the comparative analysis) is not contributed by a single architectural component, but is associated with the synergistic integration of multiple learning mechanisms; the model, through the combination of local and global feature extraction, effectively analyzed nail abnormalities from different perspectives; attention-guided fusion, on the other hand, improved feature selection and classification reliability. Hence, HEFT-Net is considered an interpretable and effective framework for automated nail disease diagnosis.

5. Conclusion, Limitations and Future Directions

5.1 Conclusion

Globally, nail diseases are a significant healthcare problem due to the associated diverse clinical appearances, visual similarities among different conditions, and the difficulty of achieving accurate diagnosis based only on visual examination. The development of automated image-based diagnostic systems can support early disease identification and improve accessibility to healthcare services, particularly in environments with limited specialized expertise. A novel Hybrid EfficientNet–Swin Transformer Network (HEFT-Net) was proposed in this study for automated multi-class nail disease diagnosis; the proposed framework integrates multiple complementary learning strategies within a unified diagnostic architecture, thereby addressing the limitations of conventional DL.

HEFT-Net hybridizes an EfficientNet-based convolutional feature extraction block with a Swin Transformer-based global contextual representation learning block to achieve both fine-grained local image properties (such as nail texture, color difference, and morphology pattern) and complex relationships between various parts of the nail image. Moreover, the proposed feature fusion mechanisms ensure selection of the most informative representations based on the problem and the input features. The main advantages of using self-supervised representation learning are:

i) Using such methods helps to better define the image feature extraction capabilities when dealing with limited medical image data,

ii) Owing to changes in the distribution of disease categories in the medical image, focal loss optimization enhances the classification performance.

To enhance transparency and clinical interpretability, Grad-CAM++ was introduced to visualize the areas contributing to the model's prediction performance; this explainability feature adds value to understanding the decision-making process and makes the proposed AI system more reliable. The experimental analysis confirmed the effectiveness of HEFT-Net for classification, with 92.5 % accuracy, 92.1 % precision, 91.8 % recall, and 91.9 % F1-score.

Finally, the ablation analysis showed that each component of the proposed framework significantly influenced the final performance; the comparative analysis showed the effectiveness of the hybrid convolutional-transformer learning strategy. In general, HEFT-Net is considered an accurate, stable, and informative tool for automatically recognizing nail diseases, with the potential of being a robust DL architecture for intelligent medical image analysis.

5.2 Limitations

The limitations of the proposed framework are identified as follows:

i.) The proposed framework was evaluated using a relatively limited nail image dataset containing 655 images distributed among 17 disease categories; although data augmentation and self-supervised learning strategies were employed to improve model generalization, the limited availability of labeled medical images may still restrict the ability of the model to represent the full diversity of nail disease appearances.

ii.) The dataset contains an unequal distribution among disease categories; some conditions contain considerably fewer samples than others, which may increase the difficulty of learning rare disease patterns. Although focal loss optimization was applied to reduce the impact of class imbalance, additional samples from underrepresented categories would further improve classification reliability.

iii.) The current framework was evaluated using image-based information only; however, in clinical settings where dermatological diagnosis often depends on patient history, physical examination, and other clinical observations, the integration of multimodal clinical information could represent a better diagnostic approach.

iv.) Grad-CAM++ highlighted image regions associated with predictions, which improved model interpretability, there is a need for further validation with experienced dermatologists. This will enable determination of the alignment between the generated explanations and clinically meaningful features.
v.) Multiple advanced DL components were combined in the proposed architecture, which increases computational load; hence, optimization strategies should be deployed before use in resource-scarce settings, such as in real-time diagnostic devices or mobile healthcare systems.

5.3 Future Directions

Several works can be considered in the future based on the performance of the proposed HEFT-Net framework:

i.) A large central clinical nail disease dataset with images should be gathered from a variety of healthcare settings, as such datasets would enhance the generalization of these models and offer more convincing evidence of their clinical usefulness.
ii.) Sophisticated semi-supervised and self-supervised learning methods that exploit the advantage of large unlabelled medical images should be explored. These strategies may lower the reliance on manual annotation and enhance the representation learning ability.
iii.) The proposed system can be extended by integrating more comprehensive clinical information, including patient demographics, medical history, and lab observations; these can form a multimodal AI system that offers more all-encompassing diagnostic assistance.
iv.) Future studies should focus on optimization methods that allow efficient deployment of the model on portable healthcare devices, such as knowledge distillation, pruning, and lightweight transformer designs.
v.) The clinical validity of HEFT-Net should be assessed via an external validation study with dermatologists; additionally, including "Grad-CAM++" explanations with experts' evaluation would provide more evidence on the usefulness of EAI in the actual diagnostic workflow. L
vi.) HEFT-Net should be taken beyond the realm of disease classification and focus on new applications for healthcare, such as early screening, disease severity estimation, treatment monitoring, and personalized clinical decision support systems.

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