# Comparative Analysis of EfficientNetV2-S, Swin Transformer-T, and ConvNeXt-Tiny for Automated Nail Disease Classification

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***Abstract*— This paper presents a novel framework for classification of nail diseases using Deep Learning models. Nail diseases such as Onychomycosis and Psoriasis are often misdiagnosed, causing serious clinical complications and delays in effective treatment. This work utilizes three Deep Learning models: EfficientNetV2-S, Swin Transformer-T, and ConvNeXt-Tiny. These models were built and compared to classify nail images into three categories: Healthy, Onychomycosis, and Psoriasis. Transfer learning is applied in all three models and fine-tuned using a public dataset of 1,463 nail images. Mixup augmentation, label smoothing, and the AdamW optimizer are used for training. The models are evaluated on a test set of 299 images. Swin Transformer-T achieves the highest classification accuracy and macro recall of 95.20%, while ConvNeXt-Tiny achieves the highest Psoriasis recall of 92.31%.**

***Index Terms*— ConvNeXt-Tiny, Deep Learning, EfficientNetV2, Nail Disease Classification, Psoriasis Detection, Swin Transformer, Transfer Learning.**

## I. INTRODUCTION

Nails play a major role in identifying various diseases ranging from mild fungal infections to severely debilitating conditions. Nail diseases are among the most frequent and misinterpreted skin conditions. Fungal infections such as Onychomycosis are caused by a fungus called dermatophyte that affects 10 percent of the global population. Patients with nail Psoriasis make up 50%–80% of persons with Psoriasis and may have nail involvement years prior to developing skin Psoriasis and joint disease.

Late diagnosis of Psoriasis has significant ramifications, as timely adoption of systemic immune-suppressive or biologic treatments can help prevent Psoriatic Arthritis (PsA) in as many as 30% of all patients with Psoriasis. PsA is known to cause irreversible joint damage and drastically reduces quality of life. Diagnosing nail disorders is difficult in rural India, where there is an average of only 1.9 dermatologists per million people, compared to 23.4 per million in urban centres.

Recent advances in Deep Learning have achieved great success in automated medical image analysis. Convolutional Neural Networks (CNNs) such as EfficientNetV2 and ConvNeXt excel at learning local features, while Vision Transformers such as the Swin Transformer capture long-range spatial relationships through hierarchical attention. However, no comprehensive comparison of these architectures for nail disease classification under consistent training protocols has been reported. This work makes three key contributions: (1) a comprehensive comparative study of EfficientNetV2-S, Swin Transformer-T, and ConvNeXt-Tiny under an identical experimental setup; (2) in-depth per-class recall analysis with special emphasis on Psoriasis diagnosis.

## II. RELATED WORK

Esteva et al. in 2017 were the first to apply deep learning to medical image classification at dermatologist level using Deep Neural Networks. Attention mechanisms, introduced by Vaswani et al. in 2017, led to Vision Transformers now widely used for medical image classification. One challenge in nail disease classification is high intra-class similarity and limited labelled data.

Le et al. published a three-class nail disease database with Healthy, Onychomycosis, and Psoriasis images. A systematic review by Marode et al. found Onychomycosis detected with high sensitivity but Psoriasis with low sensitivity due to variable nail changes. Paik et al. presented a Deep Learning system for automatic Nail Psoriasis Severity Index (NAPSI) computation from 7,054 finger images.

Transfer learning and hybrid models are most frequently used in the literature. Soguktuyu and Ata used VGG-based transfer learning to achieve 94% accuracy on nail abnormality sub-classes. Panchbhai et al. designed a DenseNet169-LSTM hybrid for Psoriasis detection with 89.9% F1-score. Boopalan and Sabtharishi used Gabor filters with AdaBoost to achieve 90.94% accuracy, providing a strong baseline for comparison.

Shandilya et al. proposed a Hybrid Capsule CNN achieving 99.25% validation accuracy across six nail disorder classes (different taxonomy). Nijhawan et al. used stable diffusion for synthetic data augmentation of Vision

Transformer training, reporting about 3.02% accuracy improvement.

## III. ARCHITECTURE OF NAIL DISEASE CLASSIFICATION SYSTEM

The study proposes comparing EfficientNetV2-S, Swin Transformer-T, and ConvNeXt-Tiny for classification of nail images into Healthy, Onychomycosis, and Psoriasis classes. All three models differ in complexity and are evaluated based on per-class recall. Psoriasis is treated with special attention given potential Psoriatic Arthritis risk. The overall architecture begins with nail image collection, followed by preprocessing, parallel training of three models, and comparative performance evaluation.

## IV. DATASET DESCRIPTION

The dataset was sourced from a Kaggle collection published by Joseph Rasanjana, providing nail images for machine learning model development. Images are categorized into Healthy, Onychomycosis, and Psoriasis classes. The dataset was divided into training, validation, and test sets as shown in Table I. The class distribution is imbalanced: Onychomycosis represents 49.6%, Healthy 21.3%, and Psoriasis 29.1% of total samples.

Table I Dataset Partition Across All Three Splits

| Split | Healthy | Onychomycosis | Psoriasis | Total |
|---|---|---|---|---|
| Training | 200 | 464 | 267 | 931 |
| Validation | 50 | 116 | 67 | 233 |
| Test | 62 | 146 | 91 | 299 |
| Total | 312 | 726 | 425 | 1,463 |

To reduce the impact of class imbalance, MixUp augmentation was applied to increase training sample diversity and help the model learn from all classes more effectively.

## V. PREPROCESSING AND AUGMENTATION

To improve model performance, several preprocessing and augmentation techniques were applied during training: random horizontal flipping, small rotations, and color jitter (brightness, contrast, saturation, hue) for different lighting conditions. Small translations and scaling were added to reduce sensitivity to position and size changes. Images were normalized with ImageNet values for stable training. MixUp augmentation (alpha=0.2) was enabled after the second epoch. Table II summarizes the preprocessing pipeline.

Table II Data Preprocessing and Augmentation Pipeline

| Preprocessing Step | Parameters |
|---|---|
| Resize + RandomResizedCrop | 256×256 to 224×224, scale 0.85–1.0 |
| RandomHorizontalFlip | p = 0.5 |
| RandomRotation | ±15 degrees |
| ColorJitter | Brightness=0.15, Contrast=0.15, Saturation=0.1, Hue=0.05 |
| RandomAffine | Translate ±10%, Scale 0.95–1.05 |
| ImageNet Normalization | mean= [0.485,0.456,0.406], std= [0.229,0.224,0.225] |
| Mixup Augmentation | Alpha=0.2, applied after epoch 2 |

## VI. MODEL ARCHITECTURES

### A. EfficientNetV2-S

EfficientNetV2-S is a CNN using Neural Architecture Search combined with compound coefficient scaling across network depth, width, and input resolution. With 20.2M parameters, it is compact yet powerful. Fused-MBConv in early stages provides GPU efficiency. The classification head is replaced by a 3-class linear layer.

### B. Swin Transformer-T

The Swin Transformer constructs hierarchical feature maps by aggregating image patches at deeper layers, partitioning them into non-overlapping windows and applying shifted window self-attention to model global context efficiently. Its attention mechanism captures diffuse discoloration across the nail plate, making it especially suitable for Onychomycosis. It uses a 768-dimensional representation with a 3-class output layer.

### C. ConvNeXt-Tiny

ConvNeXt-Tiny is a lightweight CNN using large-kernel depth-wise convolutions and transformer-inspired techniques . It employs Layer Normalization, GELU activation, 7×7 depth-wise convolutions, and an inverted bottleneck. It excels at local texture extraction, which is important for Psoriasis detection. The head is replaced with a 768-dimensional linear layer with 3 outputs.

All three models share identical training parameters: CrossEntropyLoss with Label Smoothing (ε=0.1), AdamW optimizer (lr=1e-4, weight decay=0.01), ReduceLROnPlateau scheduler (patience=3, factor=0.5), batch size 32, maximum 20 epochs with early stopping after 5 epochs, and MixUp augmentation (α=0.2) enabled after epoch 2. All models were pre-trained on ImageNet1K and trained on a single NVIDIA T4 GPU in Google Colab.

Table III Training Hyperparameter Configuration (All Models)

| Hyperparameter | Value / Setting |
|---|---|
| Loss Funtion | CrossEntropyLoss (ε=0.1) |
| Optimizer | AdamW (lr=1e-4, wd=0.01) |
| LR Scheduler | ReduceLROnPlateau (p=3, f=0.5) |
| Batch Size / Max Epochs | 32 / 20, early stopping (p=5) |
| Mixup Alpha / Pre-training | 0.2 (after epoch 2) / ImageNet1K |

## VII. RESULTS AND PERFORMANCE EVALUATION

### A. Overall Performance Comparison

A 299-image held-out test set was used to evaluate model performance. The Swin Transformer-T achieved the highest performance on all overall metrics (Table IV), correctly identifying 99.32% of Onychomycosis cases. ConvNeXt-Tiny had the highest Psoriasis recall (92.31%); EfficientNetV2-S had the lowest (85.71%), misclassifying 13 of 91 Psoriasis cases.

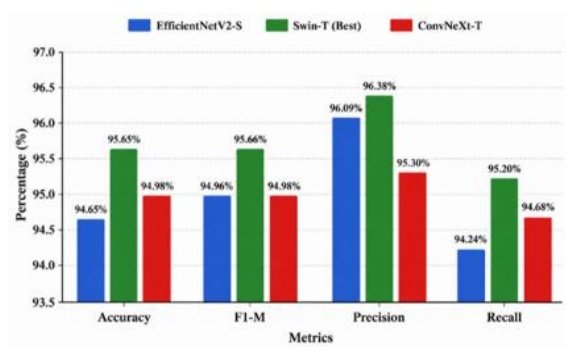


Fig. 1: Overall Performance Metrics Comparison

Table IV Overall Performance on the 299-Image Test Set

| Model | Acc. | F1-M | Prec. | Rec. |
|---|---|---|---|---|
| EfficientNetV2-S | 94.65% | 94.96% | 96.09% | 94.24% |
| Swin-T (Best) | 95.65% | 95.66% | 96.38% | 95.20% |
| ConvNeXt-T | 94.98% | 94.98% | 95.30% | 94.68% |

### B. Per-Class Recall — Key Clinical Analysis

Per-class recall results (Table V) reveal important architectural trade-offs. Swin Transformer-T achieves near-perfect Onychomycosis detection (99.32%) via global attention capturing diffuse nail discoloration. However, its Psoriasis recall of 87.91% means roughly

1 in 8 cases are missed — clinically unacceptable given that 30% of missed patients may develop Psoriatic Arthritis. ConvNeXt-Tiny provides the best Psoriasis recall at 92.31% through 7×7 depth-wise convolutions extracting fine local texture features. EfficientNetV2-S has the lowest Psoriasis recall at 85.71%.

Table V Per-Class Recall on the 299-Image Test Set

| Model | Healthy | Onycho. | Psoriasis | Macro |
|---|---|---|---|---|
| EfficientNetV2-S | 98.39% | 98.63% | 85.71% | 94.24% |
| Swin-T (Best) | 98.39% | 99.32% | 87.91% | 95.20% |
| ConvNeXt-T | 95.16% | 96.58% | 92.31% | 94.68% |

C. Confusion Matrix Analysis

The confusion matrices (Figs. 2–5) show all three models perform well on Healthy and Onychomycosis classes. The dominant error is Psoriasis cases misclassified as Onychomycosis, due to shared subungual hyperkeratosis and onycholysis features. Only 6 of 91 Psoriasis cases were missed by all three models simultaneously. Complementary error patterns indicate that an ensemble of the models may achieve better results than any individual model.

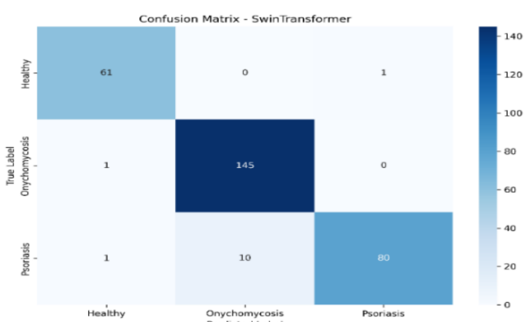


Fig. 2. Confusion Matrix Swin Transformer-T

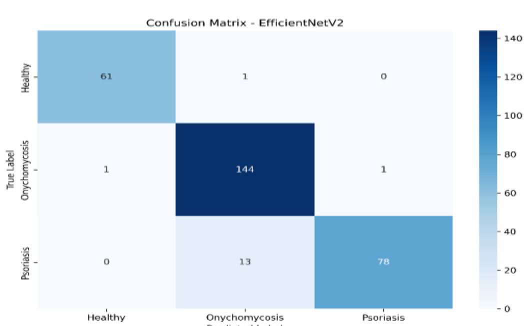


Fig. 3. Confusion Matrix — EfficientNetV2-S

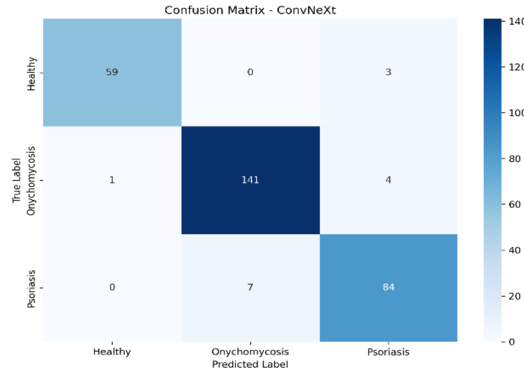


Fig. 4. Confusion Matrix — ConvNeXt-Tiny

D. Detailed Per-Model Classification Results

Tables VI–VIII present detailed per-class metrics. EfficientNetV2-S demonstrated the most stable and rapid convergence, reaching near-peak performance by epoch 7. Swin Transformer-T exhibited a longer convergence trajectory with gradual improvement through epoch 16 before early stopping. ConvNeXt-Tiny showed rapid initial convergence followed by fine-grained oscillation before stabilizing. All three models maintain high validation accuracy throughout final training rounds, confirming proper regularization with no overfitting.

Table VI Swin Transformer-T — Per-Class Performance Metrics

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Healthy | 96.83% | 98.39% | 97.60% | 62 |
| Onychomycosis | 93.55% | 99.32% | 96.35% | 146 |
| Psoriasis | 98.77% | 87.91% | 93.02% | 91 |
| Macro Avg | 96.38% | 95.20% | 95.66% | 299 |

TabLE VIIConvNeXt-Tiny — Per-Class Performance Metrics

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Healthy | 98.33% | 95.16% | 96.72% | 62 |
| Onychomycosis | 95.27% | 96.58% | 95.92% | 146 |
| Psoriasis | 92.31% | 92.31% | 92.31% | 91 |
| Macro Avg | 95.30% | 94.68% | 94.98% | 299 |

TABLE VIII. EfficientNetV2-S — Per-Class Performance Metrics

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Healthy | 98.39% | 98.39% | 98.39% | 62 |
| Onychomycosis | 91.14% | 98.63% | 94.74% | 146 |
| Psoriasis | 98.73% | 85.71% | 91.76% | 91 |
| Macro Avg | 96.09% | 94.24% | 94.96% | 299 |

## VIII. CONCLUSION

This work compares EfficientNetV2-S, Swin Transformer-T, and ConvNeXt-Tiny for nail image classification into Healthy, Onychomycosis, and Psoriasis. Swin Transformer-T achieves the best overall performance (95.65% accuracy, 95.20% macro recall). ConvNeXt-Tiny achieves the highest Psoriasis recall (92.31%), while EfficientNetV2-S is most computationally efficient. Only 6 of 91 Psoriasis cases are missed by all models simultaneously, providing strong evidence for ensemble-based approaches.

For diffuse Onychomycosis, global attention in Swin Transformer-T excels; for localized Psoriasis features, local texture convolutions in ConvNeXt-Tiny perform best. Further research will focus on weighted ensemble development, incorporating multi-institutional data for generalizability, and classifying other nail diseases such as melanonychia and nail trauma. Future work will also expand the three-class scheme to cover a wider variety of clinically relevant nail conditions.

## ACKNOWLEDGMENT

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