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ResNet152V2 - Based Deep Learning Approach for Efficient and Accurate Nail Disease Detection

Dr. Archana P, Kaushik M, Dr. Kavya T M

Assistant Professor, Dept. of CS&E, Adichunchanagiri Institute of Technology, Chikkamagaluru, Karnataka, India

P.G. Student, Dept. of CS&E, Adichunchanagiri Institute of Technology, Chikkamagaluru, Karnataka, India

Assistant Professor, Dept. of CS&E, Adichunchanagiri Institute of Technology, Chikkamagaluru, Karnataka, India

ABSTRACT: Different human nail diseases suggest a wide variety of diseases, thus an exact and prompt diagnosis is critical for healthcare and the timely provision of treatment. Traditional methods of diagnosing nail diseases involve dermatologist observation, which is time-consuming and involves subjective judgment. This paper uses deep learning and nail image recognition to create an automated nail disease classification algorithm. Specifically, a deep learning algorithm, based on CNN model ResNet152V2 with transfer learning is used to classify 13 types of diseased and healthy nail images with the target accuracy of more than 95% for each of the 13 different classes. The goal of the system is to classify the images into 13 different disease classes including healthy nails, to increase the model's accuracy and generalization through data augmentation, dropout and fine-tuning methods.

KEYWORDS: Deep learning, Convolutional Neural Networks, ResNet152V2, Nail disease classification, Transfer learning, Medical imaging, Dermatology, Image preprocessing, Feature extraction, Multi-class classification.

I. INTRODUCTION

Nail diseases among human beings may be indicative of different illnesses and thus a proper diagnosis is important for prompt treatment. Traditional approaches to nail disease diagnosis require dermatologists' manual analysis and thus could be time-consuming and biased. [1] This research will make use of deep learning and analysis of nail images in order to devise an automated classification method of nail diseases. [1] In recent years, great progress has been made regarding deep learning technology and its application in automated medical image analysis and diagnosis. This CNN model based on ResNet152V2 architecture and transfer learning classifies 13 categories of healthy and sick nails.

The reason behind the need for the work lies in the rise in the cases of nail diseases, the requirement for early and accurate diagnosis, the development of artificial intelligence and deep learning technology, the difficulties faced in manual clinical diagnosis, the excellent efficiency of deep residual networks, and the need to assist healthcare decision making. Through utilizing the strengths of the deep residual network with 152 layers, this research intends to offer an automatic tool for nail disease detection at an early stage.

II. LITERATURE SURVEY

Automated nail disease detection research has progressed tremendously through the application of deep learning approaches. For instance, the researchers in Ajmal et al. [6] used CNN as an image processing technique and achieved better accuracy than other conventional image processing approaches. Moreover, in their work Pathan et al. [5] came up with an intelligent approach for the analysis of nail images with the use of preprocessing, segmentation, feature extraction, and deep learning in order to detect disease in its early stages. In addition, Roy et al. [4] implemented a CNN-LSTM hybrid network architecture that performed better because of spatial and contextual feature learning, even though at the cost of increased computational burden.

Further improvements were made by Alzahrani et al. [2] through the introduction of a deep hybrid learning methodology that used feature extraction based on CNN together with an advanced classification process for the

accurate differentiation of visually similar nail diseases with high generalization ability. The most recent advancement in the detection of nail disease was performed by Nasra and Gupta [1] who developed an automated system based on the ResNet18 model and transfer learning for the identification of nail diseases and obtained high classification accuracy using the lightweight model. Despite the successful performance of the current approaches, problems like sensitivity to dataset quality, complexity, and lack of coverage of other nail diseases still exist.

III. METHODOLOGY

A. System Architecture

ResNet152V2 is a deep convolutional neural network that uses residual learning and skip connections to improve feature extraction and avoid vanishing gradient problems in very deep networks. It utilizes 152 deep residual layers with identity skip connections for efficient training and uses transfer learning with pre-trained ImageNet weights for better feature extraction, including batch normalization and global average pooling for stable learning and reduced overfitting.

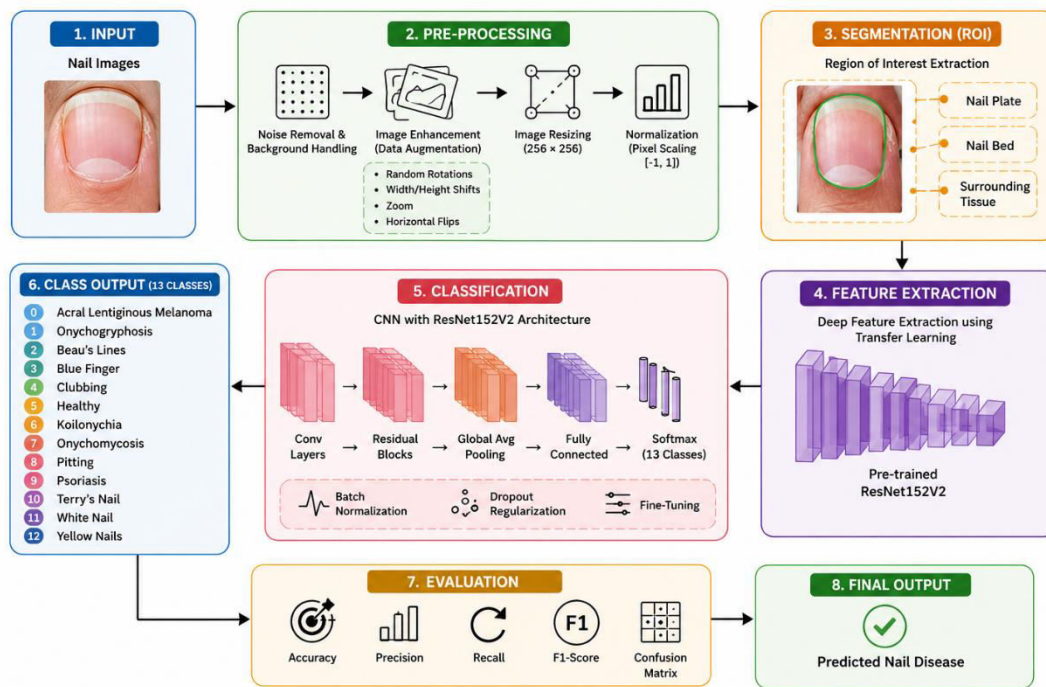


Fig.1: Proposed ResNet152V2 System architecture for Nail Disease Detection.

Fig.1 represents the proposed Nail Disease Detection System begins with nail image acquisition followed by preprocessing techniques such as noise removal, augmentation, resizing, and normalization. The segmented nail region (ROI) is then processed using a pre-trained ResNet152V2 model for deep feature extraction and classification into 13 nail disease categories. Finally, the model performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrix metrics to generate the predicted disease output.

B. Dataset Description

The study employs a labelled dataset comprising 5,502 nail disease images obtained from multiple clinical sources. They are classified as follows:

- **Acral Lentiginous Melanoma:** Nail pigmentation disorder characterized by dark longitudinal bands.
- **Onychogryphosis:** Thickened and curved nail resembling a ram's horn.
- **Beau's Lines:** Transverse depressions across the nail plate caused by interrupted nail growth.
- **Blue Finger:** Bluish discoloration of the nail due to circulatory or pigmentation abnormalities.

- **Clubbing:** Enlargement of fingertips with increased nail curvature.
- **Healthy Nail:** Normal nail appearance without any visible abnormalities.
- **Koilonychia:** Spoon-shaped nails often associated with nutritional deficiencies.
- **Onychomycosis:** Fungal nail infection causing discoloration and thickening.
- **Pitting:** Small depressions on the nail surface commonly associated with psoriasis.
- **Psoriasis:** Nail abnormalities including pitting, discoloration, and thickening.
- **Terry's Nail:** Whitish nail appearance with a narrow distal pink band.
- **White Nail:** Partial or complete whitening of the nail plate.
- **Yellow Nails:** Yellow discoloration often associated with fungal infections or systemic diseases.

The dataset consists of 13 nail disease classes and is randomly partitioned into training (80%) and testing (20%) subsets. Stratified sampling is employed to ensure proportional representation of all disease categories in both sets, thereby improving the reliability and generalization capability of the ResNet152V2-based classification model.

C. Pre-Processing and Image Enhancement

Pre-processing involves noise removal through bilateral filtering and contrast enhancement. Bilateral filtering removes unwanted camera noise while preserving important nail edges, contours and texture details. Contrast enhancement enhances local contrast and improves visibility of nail abnormalities under uneven lighting or pale background conditions. [1] Image enhancement includes data augmentation techniques such as rotation, shifting, zooming, and flipping, which artificially increase dataset diversity to improve model generalization and reduce overfitting. Rescaling and normalization involve pixel rescaling—scaling pixel intensity values to the range $[-1,1]$ for stable learning—and batch normalization, which normalizes feature distributions during training to accelerate convergence and improve stability

D. Data Augmentation

Data augmentation includes rotation with $\text{rotationrange}=30$ (random rotation up to $\pm 30^\circ$), width shift with $\text{widthshiftrange}=0.2$ (horizontal movement up to 20%), height shift with $\text{heightshiftrange}=0.2$ (vertical movement up to 20%), shear with $\text{shearrange}=0.2$ (slanting/transformation of image), zoom with $\text{zoomrange}=0.2$ (random zoom in/out up to 20%), horizontal flip with $\text{horizontalflip}=\text{True}$ (left-right flipping), and fill mode with $\text{fill_mode}=\text{'nearest'}$ (fills empty pixels after transformations).

E. Feature Extraction and Classification

The input nail image, sized at $256 \times 256 \times 3$, goes through a process of resizing and normalization. The initial convolution and pooling layers focus on extracting low-level features like edges, textures, and the boundaries of the nail. Then, we dive into residual blocks (ResNet152V2) that help in learning deep hierarchical features, utilizing skip connections to enhance how we represent these features. A global average pooling layer comes next, which reduces the dimensions of the features while still keeping the crucial information intact. Finally, a fully connected dense layer takes those extracted features and maps them to various disease classes, and a SoftMax layer provides the classification probabilities across 13 different nail disease categories, such as Healthy, Clubbing, and more.

F. Model Architecture

ResNet152V2 is a deep convolutional neural network that employs residual learning with skip connections, enabling efficient training of very deep architectures. The residual learning mechanism is expressed as:

$$y=F(x)+x \quad (1)$$

where we have x as the input, $F(x)$ representing the residual mapping, and y as the output. The architecture features an impressive 152 convolutional layers that incorporate pre-activation residual blocks, batch normalization, and ReLU activation functions. It kicks off with a 3×3 convolution layer followed by max pooling, and then dives into a series of residual blocks designed for hierarchical feature extraction. To wrap things up, a Global Average Pooling layer and a fully connected Softmax layer come into play, classifying images into 13 distinct nail disease categories. The model leverages ImageNet pre-trained weights and is fine-tuned on the nail disease dataset, enhancing both classification accuracy and generalization.

G. Training Configuration

The ResNet152V2 model is set up with the Adam optimizer, kicking off with an initial learning rate of 0.001 and using categorical cross-entropy for loss calculation. Images are resized to 256×256 pixels and processed in batches of 32. The training unfolds in two phases, each lasting 20 epochs, and is followed by fine-tuning at a learning rate of 1×10^{-5} . To enhance generalization and ward off overfitting, techniques like batch normalization, dropout (set at 0.5), early stopping, and learning rate scheduling are all put into play.

H. Evaluation Metrics

Model performance is evaluated using:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

$$\text{Precision} = \frac{TP}{(TP + FP)} \quad (3)$$

$$\text{Recall} = \frac{TP}{(TP + FN)} \quad (4)$$

$$\text{F1 - Score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (5)$$

where TP represents true positives, TN true negatives, FP false positives, and FN false negatives.

IV. EXPERIMENTAL RESULTS

The architecture we designed has undergone training for 40 epochs, utilizing the best parameter values for the optimizer. The results from this training reveal a consistent increase in model accuracy, climbing from 56% to an impressive 93% for training, and from 65% to 89% for validation. Meanwhile, the training loss has significantly decreased from 1.41 to 0.21, and the validation loss has also improved, dropping from 1.09 to 0.36. This suggests that the learning process has effectively converged. The close alignment between training and validation results highlights the model's strong generalization ability without falling into overfitting. The plots for both training and validation illustrate a stable learning trend, showcasing the effectiveness of our proposed method. Additionally, the confusion matrix reveals a good number of correct classifications along the diagonal, with only a few misclassifications appearing off-diagonal. In summary, the model has achieved a validation accuracy of around 89%, proving its ability to accurately differentiate between the target classes.

A. Analysis based on the characteristics of Epoch performance

Fig.2(a) illustrates the training and validation accuracy of the ResNet152 model over a span of 10 epochs. These accuracy curves reveal a wealth of insights into how the ResNet152 model learns and its effectiveness for various applications. At the outset of training, the ResNet152 model shows rapid improvement. Its training accuracy jumps from 68.86% in the first epoch to 83.19% in the second, and then reaches 89.52% by the third epoch. Similarly, the validation accuracy also improves, climbing from 77.22% to 81.56% across these two epochs. This indicates that the ResNet152 model excels at identifying features and learning from them. As training continues, the training accuracy keeps rising, hitting 94.50% by epoch 5 and surpassing 97% by epoch 6. By the time we reach epoch 10, the training accuracy stands at an impressive 99.36%. This is a strong indication that the ResNet152 model fits the training data exceptionally well.

However, the validation accuracy does fluctuate a bit during training, consistently remaining between 77.51% and 86.98%. The peak validation accuracy occurs at a certain epoch, suggesting that the model continues to improve its ability to predict unseen data. It's worth noting that, over time, a gap emerges between the training and validation accuracy. Nevertheless, the validation accuracy remains quite high, indicating that the model effectively applies what it has learned to make predictions. We don't observe significant issues with the ResNet152 model overfitting to the training data. Overall, the ResNet152 model demonstrates a strong capability for distinguishing between nail diseases, making it a solid choice for this type of task.

In Fig. 2(b), we can observe the training and validation loss curves over 10 epochs, giving us insight into how the model is performing as it learns. Right off the bat, the training loss drops significantly from 0.9149 in the first epoch to 0.4465 in the second, indicating that the model is picking up speed and the optimization process is on the right track. As training continues, the loss keeps decreasing, hitting 0.2202 by the end of the epoch and plummeting further to 0.0323 by the final epoch. This clearly shows that the model is effectively learning patterns from the training data.

On the validation side, the loss generally trends downward, although it does experience some fluctuations throughout the epochs. It kicks off at 0.6055, dips to 0.5107 in the second epoch, then bounces back up to 0.6721 in the next epoch before settling around 0.40–0.45 in the later stages. Notably, we see a slight uptick in validation loss around the ninth epoch, even while the training loss continues to decline. This could suggest a bit of overfitting, but the good news is that the validation loss doesn't keep rising. The model is still managing to generalize well. By the end of the training, the validation loss stands at 0.4507, while the training loss is impressively low, indicating that the model has successfully converged. Overall, the loss curves illustrate that the model is learning effectively, with stable optimization. It's capable of classifying data accurately without excessive overfitting. Both the training and validation losses are behaving as we'd hope: the training loss is decreasing, and the validation loss isn't spiking too much.

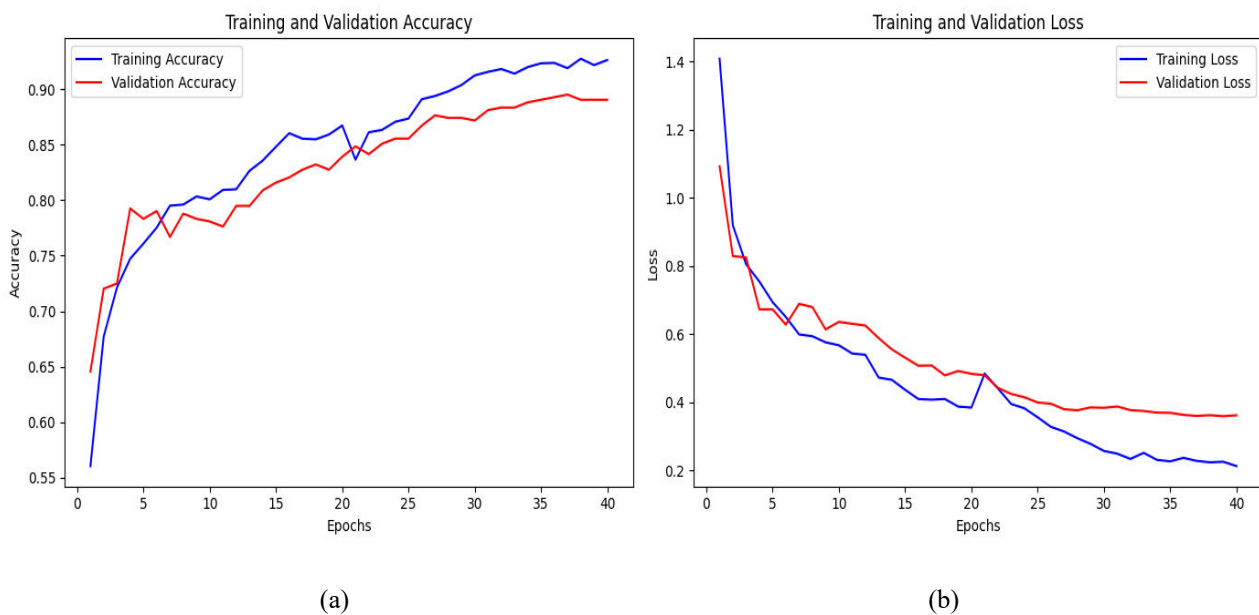


Fig.2 Training and Validation (a) Accuracy Curve (b) Loss Curve

B. Analysis based on the characteristics of the Confusion matrix

The confusion matrix shown in Fig. 3 clearly demonstrates that our proposed method performs remarkably well when it comes to categorizing the validation set. A significant number of samples are positioned along the main diagonal, which suggests that the model has accurately classified most of the nail disease categories. Notably, classes like Onychomycosis, Psoriasis, Healthy, Acral Lentiginous Melanoma, Clubbing, and Pitting saw a high number of correct predictions, indicating that the model has effectively grasped the unique features of these categories. That said, there are a few instances where the model misclassified some samples. However, these errors are relatively minor, and the overall error rate remains quite low. This clearly shows that our deep learning algorithm is quite effective in classifying nail diseases.

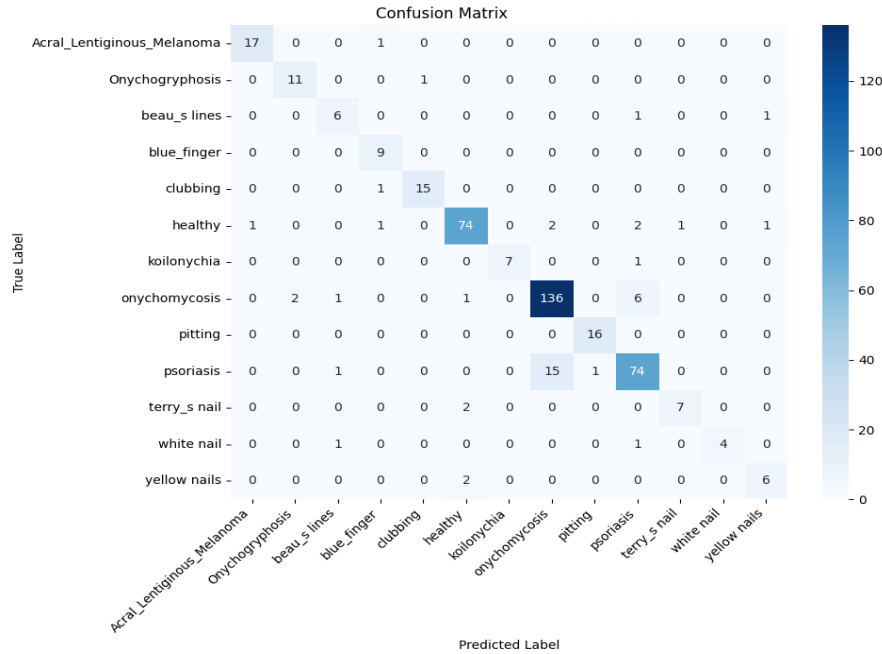


Fig.3 Confusion Matrix

C. Analysis based on Classification Parameters

TABLE I. CLASSIFICATION PARAMETERS

| Name of the Class | Precision | Recall | F1-Score | Accuracy |
|----------------------------|-----------|--------|----------|----------|
| Acral Lentiginous Melanoma | 0.99 | 0.99 | 0.99 | 0.97 |
| Onychogryphosis | 1.00 | 0.99 | 0.99 | |
| Beau's Lines | 0.95 | 0.93 | 0.94 | |
| Blue Finger | 0.96 | 0.97 | 0.96 | |
| Clubbing | 0.97 | 0.98 | 0.97 | |
| Healthy | 0.98 | 1.00 | 0.99 | |
| Koilonychia | 0.76 | 0.92 | 0.83 | |
| Onychomycosis | 0.97 | 0.96 | 0.97 | |
| Pitting | 1.00 | 1.00 | 1.00 | |
| Psoriasis | 0.94 | 0.97 | 0.96 | |
| Terry's Nail | 0.87 | 0.72 | 0.79 | |
| White Nail | 0.92 | 0.58 | 0.71 | |
| Yellow Nails | 0.68 | 0.56 | 0.61 | |

The classification performance of the proposed model on the training dataset in terms of precision, recall, F1-score, and overall accuracy is shown in Table I. The model accuracy was overall 97% with a very good learning capability and class discrimination. Several classes, including Pitting, Healthy, Acral Lentiginous Melanoma and Onychogryphosis, reached nearly perfect performance with F1-scores between 0.99 and 1.00, indicating very reliable classification. The F1-scores for Onychomycosis, Clubbing, Blue Finger and Psoriasis were also robust with values over 0.95. Koilonychia, Terry's Nail, White Nail and Yellow Nails were comparatively lower due to their smaller sample sizes and visual similarities with other nail conditions. Nevertheless, the weighted average precision, recall, and F1-score of 0.97 confirm that the proposed deep learning model effectively captures disease-specific features and provides robust multi-class nail disease classification performance.

V. CONCLUSION

This study introduces a comprehensive deep learning framework that leverages the ResNet152V2 architecture with transfer learning to automatically classify nail diseases. The goal of this system is to address the pressing need for quick, objective, and precise diagnoses of nail conditions, which have traditionally relied on dermatologists. By automating the diagnostic process, the system aims to improve accuracy and generalization through techniques like data augmentation, dropout, and fine-tuning. This provides healthcare professionals with a swift and dependable diagnostic tool for the early detection of nail diseases. The model combines advanced pre-processing methods—such as bilateral filtering, contrast enhancement, and pixel normalization—with cutting-edge deep learning architectures and transfer learning, enabling it to achieve impressive classification accuracy across a diverse array of nail disease categories.

VI. FUTURE SCOPE

Future work on the proposed nail disease classification system includes using larger and more diverse datasets to improve model generalization and robustness. Moreover, advanced deep learning architectures and ensemble techniques can be explored to improve the classification accuracy. The model can also be embedded in mobile applications for real-time diagnosis and clinical assistance. Furthermore, the implementation of explainable AI methods and the broad clinical validation will enhance the reliability and practical usability of the system in healthcare settings.

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