



Transfer Learning-Based Deep Learning Framework for Medicinal Plant Leaf Analysis and Disease Detection

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ABSTRACT

Medicinal plants play a significant role in both conventional and modern medical procedures, it is imperative that their leaves be accurately observed. Examining medicinal plant leaves by hand is time-consuming and prone to human error, especially when trying to spot early signs of illness. This research suggests using a transfer learning-based deep learning approach based on a pre-trained ResNet50 model to analyze photos of medicinal plant leaves in order to solve this issue. The experimental evaluation of this work was conducted using a standard dataset of leaf images from medicinal plants. Three classes representing healthy leaves and two main illness states were created from the dataset. All the images were scaled prior to the application of any preprocessing technique like data augmentation and normalization. The final classification layers were used to train the classification layers for a three-class classification problem with the convolutional part of the pre-trained ResNet50 network. The transfer learning approach based on feature extraction can prevent overfitting and improve the efficiency of learning for datasets of moderate sizes. Experimental findings demonstrate that the developed framework effectively captures meaningful feature representations and achieves reliable classification performance for medicinal plant analysis. The work has verified that the transfer learning approach using ResNet50 is a robust and efficient method for the automatic medicinal plant leaf monitoring and intelligent plant health evaluation.

Keywords: Transfer Learning, Medicinal Plant, Feature Extraction, ResNet50, Leaf Image Analysis.

1. Introduction

Medicinal plants are very important in the health care system because of their medicinal values. The health status of the leaves of medicinal plants affects their quality, productivity, and medicinal values. Early assessment of the health status of the leaves is important for the detection of diseases and sustainable growth of medicinal plants. However, it requires a lot of time and errors in the process of analyzing plant leaves manually, especially when there are minute differences between healthy and infected leaves. Deep learning techniques and artificial intelligence methods have improved significantly in terms of the accuracy of plant image analysis and detection of diseases. Convolution-based deep models have demonstrated strong

capability in identifying complex patterns within plant leaf images, enabling accurate analysis of disease characteristics. [1]. Because deep learning techniques can learn hierarchical feature representations straight from actual image data, they have proven to perform better in agricultural image analysis [2].

However, one of the biggest challenges in the analysis of the leaves of medicinal plants is the unavailability of large-scale labeled datasets. Most of the publicly available plant datasets are dominated by common agricultural crops, while the datasets for medicinal plants are relatively smaller and unexplored. Training deep neural networks on moderate-sized datasets often results in overfitting and poor generalization performance [3]. To overcome this problem, transfer learning has been identified as an effective solution that uses pre-trained models to enhance performance on domain-specific tasks with smaller datasets [4].

Among the many deep learning models, ResNet50 has received considerable attention owing to its deep residual learning architecture and excellent feature extraction abilities. The residual learning property of ResNet50 helps in the efficient flow of gradients and allows the model to extract discriminative features like leaf texture, shape, and disease symptoms. It has been observed in previous studies that the use of ResNet-based models for transfer learning helps in achieving robust results for plant leaf classification and disease analysis, especially when dealing with medium-sized datasets [5].

Inspired by these developments, this research work proposes a transfer learning approach for the analysis of medicinal plant leaf images based on a pre-trained ResNet50 model. The image samples of medicinal plant leaves, acquired from the Mendeley Data repository, containing around 800 labeled images, is used for the experimental analysis. The dataset is divided into three classes, which include healthy leaves and two prominent disease states. Through the use of feature extraction by freezing the convolutional layers and training the classification layers, this proposed method seeks to provide efficient analysis of medicinal plant leaf conditions for intelligent plant health monitoring.

2. Literature Review

Recently, there has been an increasing trend in the application of deep learning methods, specifically Convolutional Neural Networks (CNNs), in the analysis of plant leaf images for automated classification and disease detection. Deep learning algorithms have proved to be more effective than traditional machine learning methods in extracting intricate visual features from plant leaf images, making them an ideal choice for plant health monitoring systems [6]. The capability of CNNs to learn hierarchical features such as texture, color, and morphology has greatly improved the accuracy of plant leaf analysis tasks.

Transfer learning has been widely used in agricultural image processing to overcome the issue of limited dataset availability. It has been observed that the use of pre-trained deep learning models improves the performance of classification tasks while minimizing training time and complexity [7]. Specifically, transfer learning helps to adapt pre-trained models on large datasets, such as ImageNet, to domain-specific tasks like plant leaf classification and disease analysis.

Some authors have investigated the effectiveness of deep feature extraction based on pre-trained CNN models for plant leaf image datasets. Shafik et al. [8] conducted a study on transfer learning based on various pre-trained models and concluded that deep feature extraction is an effective technique for improving the generalization capability of models, particularly for medium-sized datasets. Hassan et al. [9] showed that CNN models based on transfer learning outperform models trained from scratch for plant leaf disease classification tasks.

Among the different deep learning models, ResNet50 has received significant attention for its deep residual learning approach and superior feature extraction ability. The residual learning approach in ResNet50 reduces the vanishing gradient problem and enables the network to learn effective discriminative features from leaf images [10]. Recent research work has validated that ResNet-based transfer learning models perform better than conventional CNN models for agricultural image classification tasks because of their deeper representation ability and improved convergence properties [11].

Moreover, data preprocessing and augmentation methods have been identified as critical elements in enhancing the robustness of deep learning models for leaf image analysis. It has been found that methods such as image resizing, normalization, rotation, and flipping can help increase the diversity of the dataset and prevent overfitting, especially when dealing with standard datasets of moderate size [12]. Data preprocessing methods are particularly important when dealing with medicinal plant leaf datasets, which tend to be smaller in size compared to agricultural datasets.

3. Proposed Methodology

This work introduces a transfer learning framework that utilizes a pre-trained ResNet50 network to analyse medicinal plant leaf images. The complete approach involves five major steps: dataset acquisition, image preprocessing, data augmentation, feature extraction from a pre-trained convolutional neural network, and final classification. This approach has been developed to analyze medicinal plant leaf conditions effectively while reducing overfitting and complexity, especially when dealing with a moderate-sized dataset. This model consist of medicinal plant leaf images can be categorised into, Healthy leaf, Leaf spot Disease, Leaf Blight Disease.

3.1 Data Source

The experimental study utilizes an open-access collection of medicinal plant leaf images obtained from the Mendeley Data repository. The dataset contains approximately 800 labelled samples representing different leaf conditions. For the purpose of classification, the images are grouped into three categories: healthy leaf, leaf spot, and leaf blight. To ensure reliable evaluation, the data is partitioned into training, validation, and testing subsets using an appropriate split ratio. This division supports balanced learning and improves the model's generalisation capability.

3.2 Image Preprocessing and Augmentation

Data preprocessing is crucial in deep learning for image analysis. Leaf images were resized to 224×224 pixels for the ResNet50 model, and normalization was carried out to standardize pixel values, enhancing model training. Additional methods such as noise removal and image standardization ensured dataset uniformity, allowing the model to focus on leaf characteristics like texture, color patterns, and disease areas.

3.3 Algorithm for Transfer Learning-Based Medicinal Leaf Analysis

The proposed methodology integrates transfer learning with a bio-inspired optimization strategy for effective medicinal plant leaf classification. The overall framework consists of image preprocessing, deep feature extraction using a pre-trained ResNet50 model, and feature optimization using the Adaptive Salp Swarm Algorithm (SSA). This combination enables efficient extraction and selection of discriminative features, improving classification performance. The overall architecture of the developed Adaptive SSA-ResNet50 framework is illustrated in Figure 1. The pre-trained ResNet50 network is employed to extract deep feature representations from the pre-processed leaf images. The Adaptive Salp Swarm Algorithm is applied to

optimize the obtained features by selecting the most relevant feature set. The fully connected layers receive the optimized attributes, which are then classified as healthy and unhealthy.

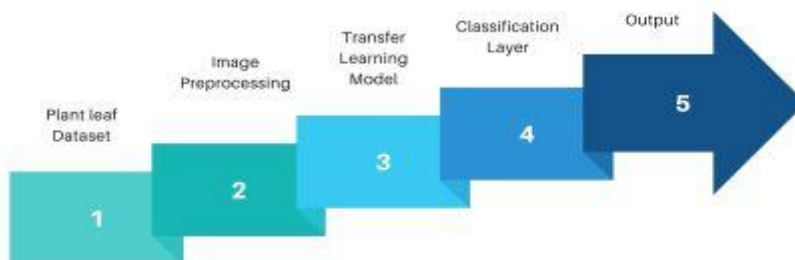


Figure.1. Conceptual Framework for Medicinal Leaf Classification

Proposed algorithm Steps (Adaptive Salp Swarm Algorithm Based Feature Optimization with ResNet50)

Input: Dataset $D=\{(x_i,y_i)\}$

Output: Predicted class label \hat{y}

Load dataset D

Perform resizing and normalization

Split D into training, validation, and testing sets

Load ResNet50 network

Remove top layers and freeze convolution layers

Extract deep features F from dataset

Initialize salp population S

Define fitness function based on classification accuracy

Set maximum iterations T

for t = 1 to T do

 Update adaptive parameter c1

 Update leader position

 Update follower positions

 Evaluate fitness of each salp

 Update global best solution

end for

Select optimal feature subset F_{opt}

Train classifier using F_{opt}

Apply Dense, Dropout, and Softmax layers

Evaluate model on test set

Predict class label \hat{y}

return \hat{y}

The proposed algorithm combines deep learning with adaptive bio-inspired optimization to improve feature selection and classification accuracy. The ResNet50 model is used to extract deep feature representations from leaf images, capturing important visual characteristics such as texture, color variations, and disease patterns. The Adaptive Salp Swarm Algorithm is then applied to optimize the extracted features. The algorithm follows a leader–follower mechanism, where the leader guides

the search process and followers update their positions accordingly. The adaptive parameter dynamically balances exploration and exploitation, enabling efficient identification of the most relevant feature subset. The optimized features are subsequently used for classification, resulting in improved accuracy and reduced redundancy. This approach enhances the overall robustness and reliability of the model for medicinal plant leaf classification.

4. Performance Evaluation and Analysis

Model training was assessed through accuracy and loss behavior. The observed trends reflect progressive improvement in learning over successive epochs. The close alignment between validation and training accuracy suggests that the model effectively generalizes to new data. The findings demonstrate that the developed framework of using a transfer learning-based ResNet50 model is effective in learning deep features from medicinal plant leaf images.

Table 1 Class-Level Performance Assessment of the Developed Framework

Class	Precision Rate (%)	Sensitivity (%)	F1-Measure (%)
Healthy Leaf	95.10	94.60	94.85
Leaf Spot Disease	93.40	92.90	93.15
Leaf Blight Disease	92.90	94.80	93.84

Feature extraction contributes to minimizing overfitting while improving generalization capability, making the model suitable for datasets with limited sample size. The class-wise performance of the model is well balanced, proving that it can differentiate between healthy and diseased leaves. The performance of the developed framework for each class is depicted in Table 1. The algorithm was able to distinguish between healthy and unhealthy states of the leaves, as indicated by the results. The consistent F1 measure across all classes reflects the reliability and stability of the developed framework. In addition, the validation trend closely aligns with the training trend, indicating that the model does not exhibit overfitting. The variation in model accuracy during both training and validation phases is depicted in Figure 2. The accuracy increases steadily, indicating the effectiveness of discriminative feature learning from images of medicinal plant leaves. The training and validation loss curves are shown in Figure 3. The loss steadily drops as the number of epochs increases, demonstrating successful model parameter optimization. Stable convergence and little overfitting are confirmed by the training and validation losses' tight alignment.



Figure 2. Variation of Model Accuracy During Training and Validation

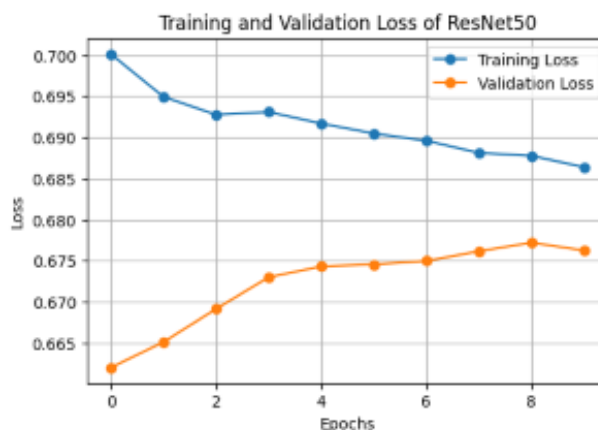


Figure 3. Model Loss Behavior Across Training and Validation phase

5. Conclusion and Future Directions

The developed framework employs a transfer learning strategy to analyze medicinal plant leaf images using deep feature representations. With this proposed model, effectively analyse and classify medicinal plant leaves into healthy and diseased states. The developed framework employs a transfer learning strategy to analyse medicinal plant leaf images using deep feature representations. The framework emphasizes adaptive feature refinement, which differentiates it from conventional deep learning approaches that rely solely on feature extraction. Future work can focus on extending the dataset and exploring advanced deep learning architectures to further enhance accuracy. Additionally, real-time implementation can be considered for practical agricultural applications. Furthermore, it is possible to integrate this proposed model with mobile or IoT-based agricultural monitoring systems to increase its practicality in real-world applications.

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