

Research Article

Comparative Evaluation of Transfer Learning CNN Architectures and Optimizers for Chinese Herbal Leaf Recognition

Lyu SiQian¹, Heshalini Rajagopal^{1*}, Muhammad Amirul Aiman Asri¹, Zaris Izzati Mohd Yassin¹, Peng Lean Chong², Norrima Mokhtar³

¹Department of Computing, School of Engineering and Computing, MILA University, 71800 Nilai, Negeri Sembilan, Malaysia

²UNIRAZAK Innovative Methods & Projects Powered By AI & Cutting-Edge Technology (URIMPACT), Universiti Tun Abdul Razak (UNIRAZAK), 50400 Kuala Lumpur, Malaysia

³Department of Electrical Engineering, Faculty of Engineering, Universiti Malaya, 50603 Kuala Lumpur, Malaysia.

Email: L.S.: 1002400058@scholar.mila.edu.my, H.R.: heshalini.rajagopal@mila.edu.my, MAM: amirul.aiman.private@gmail.com, Z.I.M.Y.: zaris.yassin@mila.edu.my, P.L.C.: keith.chong@mila.edu.my, N.M.: norrimamokhtar@um.edu.my

*Corresponding Author

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ABSTRACT

Accurate recognition of Chinese herbal leaves is essential in safeguarding the effectiveness of traditional medicinal practices, maintaining product quality standards, and preserving valuable plant biodiversity. Conventional identification approaches mainly depend on human expertise, which can be laborious, inconsistent, and vulnerable to classification errors. Furthermore, many computer-based recognition systems still face challenges in differentiating leaves with highly similar textures, venation patterns, and shapes. This study investigates an optimized training configuration for a ResNet-50 transfer learning model for automated Chinese herbal leaf recognition. The classification performance of five established convolutional neural network (CNN) architectures, namely ResNet-50, EfficientNet-B0, GoogLeNet, SqueezeNet, and DarkNet-53, was compared across 13 categories of Chinese medicinal leaves. The original dataset comprised 520 images, which were first divided into training and testing subsets using an 80:20 stratified split. Image augmentation was subsequently applied exclusively to the training subset to increase training diversity. The models were evaluated using accuracy, precision, recall and F1-score, while Adam, RMSprop, and stochastic gradient descent with momentum (SGDM) were compared using a common initial learning rate of 0.0001 and a batch size of 40. Experimental results showed that ResNet-50 trained using Adam achieved the best overall classification performance, with an accuracy of 0.911, precision of 0.901, recall of 0.910, and F1-score of 0.896. EfficientNet-B0 trained using RMSprop also demonstrated competitive performance, achieving an accuracy of 0.899 and the recall of 0.909. In contrast, SGDM generally produced lower performance across most evaluated architectures. These findings demonstrate that optimizer effectiveness is dependent on the CNN architecture and indicate that the ResNet-50 transfer learning model with Adam provides a promising approach for automated Chinese herbal leaf recognition.

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1. Introduction

Traditional Chinese Medicine (TCM) has long utilized medicinal plants as a primary source of therapeutic treatment, and the demand for herbal-based remedies continues to expand worldwide due to their perceived health benefits and natural origin [1]. Ensuring the correct identification of medicinal plants is therefore essential to maintain treatment effectiveness, product consistency, and consumer safety [2]. Nevertheless, distinguishing herbal species accurately remains challenging because many leaves exhibit highly similar shapes, textures, and venation characteristics. Errors in plant identification may result in reduced medicinal efficacy, inappropriate treatment, or

potential health risks, highlighting the importance of developing reliable recognition systems [3]. Recent progress in artificial intelligence and computer vision technologies has opened new opportunities for automating herbal plant classification with improved consistency and efficiency [4]. Among these technologies, deep learning approaches based on Convolutional Neural Networks (CNNs) have demonstrated exceptional capability in extracting discriminative image features and recognizing complex visual patterns [1][5]. When combined with transfer learning, CNN-based systems can adapt knowledge learned from large-scale benchmark datasets to specialized image recognition tasks with limited training samples. This strategy minimizes the requirement for extensive manually collected datasets while reducing

computational cost and training duration [6][7]. Several modern deep learning architectures, including ResNet-50 and YOLO-based frameworks, have reported encouraging performance in plant and medicinal herb recognition applications, providing a more objective alternative to traditional manual identification techniques [8][9]. Despite these developments, automated classification of herbal leaves remains a demanding task because of variations in lighting conditions, leaf orientation, texture complexity, and inter-species similarity [10]. Consequently, further investigation is required to determine suitable deep learning architectures and training configurations for reliable Chinese herbal leaf recognition.

To address these challenges, this study investigates a transfer learning approach for the automated recognition of 13 categories of Chinese medicinal leaves. Five established CNN architectures, namely ResNet-50, EfficientNet-B0, GoogLeNet, SqueezeNet, and DarkNet-53, are comparatively evaluated to determine their classification capabilities for the target dataset. To increase training diversity, image augmentation techniques are applied to the training data. Model performance is evaluated using accuracy, precision, recall and F1-score to provide a comprehensive comparison among the investigated architectures.

In addition, this research performs a comparative investigation of three optimization algorithms, namely Adaptive Moment Estimation (Adam), Root Mean Square Propagation (RMSprop), and Stochastic Gradient Descent with Momentum (SGDM), to identify the most suitable optimizer for enhancing transfer learning performance in Chinese herbal leaf classification. The findings are expected to contribute toward the development of an efficient and scalable automated recognition approach that can support herbal practitioners, researchers, and pharmaceutical applications in improving the identification and authenticity assessment of traditional Chinese medicinal plants.

2. Methodology

2.1. Image Dataset

A publicly accessible herbal leaf image dataset containing 520 original images representing 13 distinct Chinese medicinal leaf species was utilized in this study [11]. Representative samples of six different leaf categories are illustrated in Figure 1. Before data augmentation, the original images were divided into training and testing subsets using an 80:20 stratified split at the original-image level. Image augmentation was then applied exclusively to the training subset to improve dataset variability and model robustness, while the testing subset remained as original images. Table 1 shows the quantity of each leaf type. Several augmentation operations were applied, including random rotation, scaling, horizontal shifting, and vertical shifting, in order to simulate variations in leaf orientation, size, and positioning. The augmentation configurations implemented in this work are summarized in Table 2.

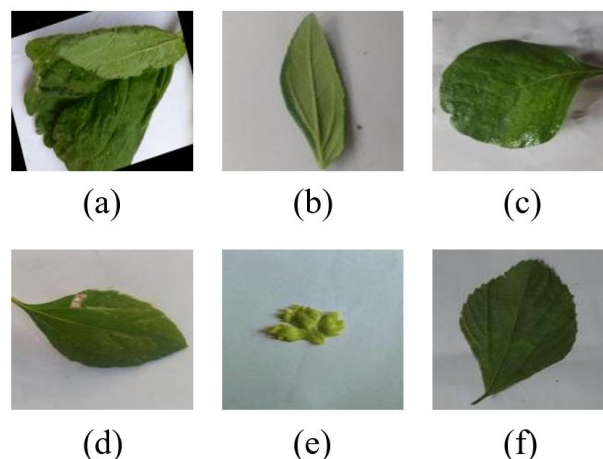


Figure 1 Sample of 6 Chinese Herbal Leaf Species (a) *Amaranthus Viridis*, (b) *Euphorbia Hirta*, (c) *Amaranthus Dubius*, (d) *Tridax Procumbens*, (e) *Coriandrum Sativum* and (f) *Acalypha Indica*

Table 1 Number of Image Samples for each Species

Herbal Leaf Species	Quantity
<i>Amaranthus viridis</i>	40
<i>Euphorbia hirta</i>	40
<i>Amaranthus dubius</i>	40
<i>Tridax procumbens</i>	40
<i>Coriandrum sativum</i>	40
<i>Murraya koenigii</i>	40
<i>Plectanthis amboinicus</i>	40
<i>Moringa oleifera</i>	40
<i>Acalypha reptans</i>	40
<i>Acalypha wilkesiana</i>	40
<i>Andrographis paniculata</i>	40
<i>Tinospora cordifolia</i>	40
<i>Acalypha indica</i>	40
Total	520

Table 2 Detail of Augmentation

Type of Augmentation	Range
Rotation	0-360°
Scaling	1-3
Horizontal Translation	0-50
Vertical Translation	0-50

2.2. Pre-Trained Deep Learning Models

In this study, five established pre-trained convolutional neural network architectures, namely ResNet-50, EfficientNet-B0, GoogLeNet, SqueezeNet, and DarkNet-53, were implemented and evaluated for Chinese herbal leaf classification. A summary of the architectural characteristics of each model is provided in Table 3. Model development and training were conducted using the

MATLAB Deep Network Designer platform. Consistent experimental settings were applied across all architectures, with a batch size of 40 and epoch of 60. To provide a fair comparison among the optimization algorithms, Adam, RMSprop, and Stochastic Gradient Descent with Momentum (SGDM) were evaluated using a fixed learning rate of 0.0001. All remaining training parameters were maintained consistently across the evaluated configurations. The prepared dataset was divided into 80% for model training and 20% for testing purposes. Since the dataset consisted of 13 herbal leaf categories, the original output layers of all pre-trained networks were modified and replaced with a softmax classification layer containing 13 output classes. Model effectiveness was assessed based on testing accuracy, precision, recall and F1-score. The architecture of ResNet-50 is illustrated in Figure 2.

Table 3 Pre-Trained Deep Learning Model

Model	Input Size	Depth	Architecture Type
DarkNet-53	256*256*3	53	YOLOv3 backbone network
EfficientNet-B0	224*224*3	82	Compound-scaled CNN (depth, width, resolution)
GoogLeNet	224*224*3	22	Inception-based CNN (multi-scale filters)
ResNet-50	224*224*3	50	Residual network with skip connections
SqueezeNet	227*227*3	18	Lightweight CNN with “fire” modules

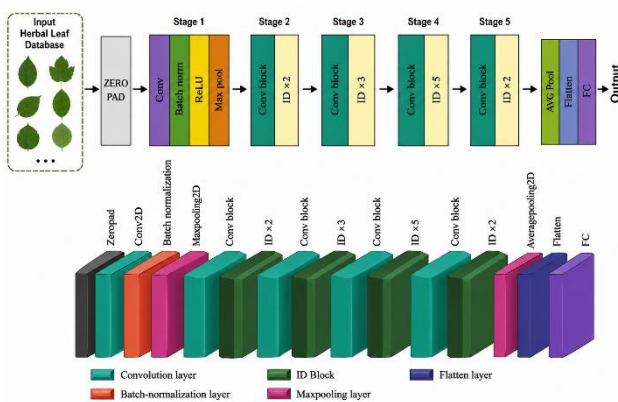


Figure 2 Resnet-50 Architecture

2.3. Evaluation Metrics and Optimizer Comparison

The trained models were assessed using several performance indicators, including testing accuracy, precision, recall, and F1-score to provide a comprehensive evaluation of classification effectiveness. Furthermore, a comparative analysis involving three optimization algorithms, namely Adaptive Moment Estimation (Adam), Root Mean Square Propagation (RMSprop), and Stochastic Gradient Descent with Momentum (SGDM), were conducted using a fixed learning rate of 0.0001. The objective of this comparison was to examine the interaction between CNN architecture and optimizer under consistent training settings rather than to establish the universal superiority of a particular optimization algorithm.

3. Results and Discussions

Table 4 presents the test-set classification performance of five pre-trained CNN architectures, namely ResNet-50, EfficientNet-B0, GoogLeNet, SqueezeNet, and DarkNet-53, trained using Adam, RMSprop, and stochastic gradient descent with momentum (SGDM). To provide a consistent comparison, all experiments were conducted using an initial learning rate of 0.0001, epoch of 60 and a batch size of 40. The models were evaluated in terms of accuracy, precision, recall, and F1-score. The results demonstrate that classification performance was influenced by the combination of CNN architecture and optimizer, with no single optimization algorithm consistently producing the best performance across all evaluated architectures.

Among the models trained using Adam, ResNet-50 achieved the highest overall performance, with an accuracy of 0.911, precision of 0.901, recall of 0.910, and F1-score of 0.896. This configuration also achieved the highest accuracy, recall and F1-score among all architecture-optimizer combinations evaluated in this study. EfficientNet-B0 trained using Adam also demonstrated strong performance, achieving an accuracy of 0.880 and the highest precision of 0.983. In contrast, SqueezeNet achieved the lowest accuracy among the Adam-based configurations at 0.734.

Under RMSprop optimization, EfficientNet-B0 achieved the strongest performance, obtaining an accuracy of 0.899, precision of 0.887, recall of 0.909, and F1-score of 0.889. ResNet-50 maintained competitive performance under RMSprop, with an accuracy of 0.880, precision of 0.840, recall of 0.872 and F1-score of 0.837. In comparison, SqueezeNet recorded the lowest accuracy under RMSprop at 0.709, precision of 0.618, recall of 0.714 and F1-score of 0.628. These findings indicate that both ResNet-50 and EfficientNet-B0 were comparatively effective when combined with adaptive optimization methods, although their optimal optimizer differed.

SGDM generally resulted in lower classification performance than Adam and RMSprop for several of the evaluated architectures. Among the SGDM-based models, DarkNet-53 achieved the highest performance, with an accuracy of 0.854, precision of 0.829, recall of 0.826, and

F1-score of 0.803. In contrast, EfficientNet-B0 and SqueezeNet achieved substantially lower accuracies of 0.354 and 0.481, respectively. The considerable variation observed under SGDM further demonstrates that optimizer effectiveness is dependent on the characteristics of the CNN architecture rather than being universally consistent across models.

The strong performance of ResNet-50 with Adam may be associated with the residual learning mechanism of ResNet-50, which facilitates gradient propagation through deeper network layers and supports effective feature learning [12][13]. This characteristic may be advantageous for distinguishing Chinese herbal leaves that exhibit subtle differences in shape, texture, and venation patterns. EfficientNet-B0 also demonstrated competitive performance, particularly with RMSprop, which is consistent with its efficient feature representation and parameter utilization reported in previous image-classification studies [14]. The competitive performance of ResNet-50 and EfficientNet-B0 observed in this study is also consistent with previous transfer learning studies involving plant image classification [15]. However, the substantial performance differences observed when different optimizers were applied to the same architecture indicate that architectural capability alone does not determine classification performance.

Overall, ResNet-50 trained using Adam was identified as the best-performing configuration, achieving the highest accuracy of 0.911, recall of 0.910 and F1-score of 0.896 among all evaluated combinations. Nevertheless, Adam was not universally superior, as EfficientNet-B0 achieved its strongest performance when trained using RMSprop, while DarkNet-53 performed best under SGDM. Therefore, the results demonstrate that optimizer selection should be considered together with CNN architecture when developing transfer learning models for Chinese herbal leaf classification. Based on its superior overall classification performance, ResNet-50 trained using Adam was selected as the final training configuration in this study.

Table 4 Test-Set Performance of the Best-Performing CNN Architectures Across Optimizers and Learning Rates

Model	Best Epoch	Acc.	P	R	F1
Adam Optimizer					
SqueezeNet	40	0.734	0.715	0.692	0.664
DarkNet-53	30	0.835	0.802	0.846	0.802
EfficientNet-B0	40	0.880	0.983	0.892	0.878

GoogLeNet	50	0.817	0.794	0.832	0.801
ResNet-50	50	0.911	0.901	0.909	0.896
RMSprop Optimizer					
SqueezeNet	60	0.709	0.618	0.714	0.628
DarkNet-53	40	0.760	0.719	0.771	0.711
EfficientNet-B0	60	0.899	0.887	0.910	0.889
GoogLeNet	30	0.823	0.791	0.822	0.796
ResNet-50	40	0.880	0.840	0.872	0.837
SGDM Optimizer					
SqueezeNet	60	0.481	0.523	0.470	0.427
DarkNet-53	40	0.854	0.829	0.826	0.803
EfficientNet-B0	60	0.354	0.292	0.296	0.281
GoogLeNet	60	0.696	0.630	0.615	0.597
ResNet-50	50	0.747	0.701	0.735	0.677

Acc. = Accuracy, P = Precision; R = Recall, F1 = F1 Score

4. Conclusion

This study presented a comparative investigation of five pre-trained convolutional neural network architectures, namely DarkNet-53, EfficientNet-B0, GoogLeNet, ResNet-50, and SqueezeNet, for the recognition of 13 categories of Chinese herbal leaves using an augmented dataset. The models were evaluated using Adam, RMSprop, and stochastic gradient descent with momentum (SGDM) under a common initial learning rate of 0.0001, epoch of 60 and batch size of 40. The experimental results demonstrated that classification performance was influenced by the interaction between the CNN architecture and the selected optimizer.

Among all evaluated architecture-optimizer configurations, ResNet-50 trained using Adam achieved the highest overall classification performance, with an accuracy of 0.911, precision of 0.901, recall of 0.910, and F1-score of 0.896. EfficientNet-B0 trained using RMSprop also demonstrated competitive performance, achieving an

accuracy of 0.899 and recall of 0.909, while EfficientNet-B0 trained using Adam achieved the highest precision of 0.983. In comparison, SGDM generally produced lower classification performance across most architectures, although DarkNet-53 remained comparatively effective under SGDM with an accuracy of 0.854. These findings confirm that no optimizer was consistently superior across all CNN architectures and that optimizer effectiveness is dependent on the characteristics of the underlying network.

Based on the comparative evaluation, ResNet-50 with Adam was selected as the final training configuration because it achieved the highest accuracy and F1-score among all evaluated combinations. In this study, the optimization of ResNet-50 therefore refers to the selection of an effective training configuration rather than modification of the original ResNet-50 architecture. The results demonstrate the potential of ResNet-50 transfer learning for automated Chinese herbal leaf recognition while also highlighting the importance of selecting an appropriate optimizer for a particular CNN architecture.

Overall, the evaluated transfer learning models demonstrate strong potential for Chinese herbal leaf recognition. However, the reported findings are limited by the small original dataset. Future work will focus on collecting additional independent samples, expanding the dataset to include additional medicinal plant species, evaluating attention-based and hybrid CNN–Transformer models, and deploying lightweight models on mobile and embedded platforms.

5. Future Work

Based on the findings and current limitations of this study, several directions are proposed to further enhance the capability and applicability of the selected ResNet-50 transfer learning model. First, future research will focus on expanding the dataset to include more than 100 species of Chinese medicinal plants. Additional image samples captured under diverse environmental conditions, viewpoints, lighting settings, and seasonal variations will be collected to improve dataset diversity and model robustness. Besides leaf images, other medicinal plant components such as roots, stems, flowers, and fruits may also be incorporated to establish a comprehensive large-scale Traditional Chinese Medicine (TCM) herbal image database representing real-world scenarios.

Second, future model development will investigate the integration of attention mechanisms into ResNet-50 and other competitive architectures such as EfficientNet-B0 to improve feature extraction for morphologically similar herbal species. Hybrid deep learning frameworks combining Convolutional Neural Networks (CNNs) with Transformer-based architectures may also be explored to enhance both local and global feature representation and improve classification performance.

Third, model optimization techniques such as network pruning, quantization, and knowledge distillation will be considered to reduce computational complexity and

memory consumption. These approaches will facilitate the deployment of the optimized recognition model on mobile devices, embedded systems, and edge-AI platforms, enabling the development of a real-time intelligent herbal recognition application suitable for practical field use.

In addition, the functionality of the proposed system can be extended beyond species recognition by incorporating modules related to medicinal properties, herbal origin verification, and quality assessment. The integration of Internet of Things (IoT) and blockchain technologies may further support the development of a transparent end-to-end quality monitoring framework for Traditional Chinese Medicine herbs, ensuring product authenticity, traceability, and safety throughout the supply chain.

Finally, future investigations may explore advanced learning strategies, including self-supervised learning, few-shot learning, and improved optimization algorithms, to address the challenge of limited labeled data for rare or endangered medicinal plants. These approaches have the potential to improve model generalization capability while contributing toward the sustainable preservation and utilization of valuable medicinal plant resources.

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Authors Introduction

Mr. Lyu SiQian



He got his bachelor's degree in Electronic and Information Engineering from Haikou University of Economics in China in 2020. Currently, he's a master's student at MILA University in Malaysia. His research focuses on AI and image processing.

Dr. Heshalini Rajagopal



She received her PhD and Master's degree from the University of Malaya, Malaysia in 2021 and 2016, respectively. She is an Assistant Professor in the School of Engineering and Computing, MILA University. Her research interests include image processing, artificial intelligence and IoT.

Mr. Muhammad Amirul Aiman Asri



He received the B.Eng. degree in Electrical Engineering from Universiti Malaya in 2020 and the M.Eng.Sc. degree in Applied Control and Robotics in 2026. His research interests include computer vision, deep learning, image analysis, and artificial intelligence, particularly in object detection, semantic segmentation, and image quality assessment.

Dr. Zaris Izzati Mohd Yassin



She holds a Ph.D. in Electrical Engineering from Universiti Teknologi Malaysia, supported by earlier qualifications in Electrical Engineering at both the Master's and Bachelor's levels from Universiti Tun Hussein Onn Malaysia. She is currently serving as a lecturer at MILA University. Her research interests center on power quality, hotspot analysis and artificial neural network.

Ir. Peng Lean Chong



He is currently Director, Research & Partnership at UNIRAZAK Innovative Methods & Projects Powered By AI & Cutting-Edge Technology (URIMPACT), Universiti Tun Abdul Razak (UNIRAZAK). He is certified as an International Professional Engineer (IntPE) and as a Chartered Engineer (CEng) from the Engineering Council, EC and Institute of Engineering and Technology, IET, United Kingdom. His research interests include semiconductor devices, renewable energy harvesting, IoT, and computing.

Dr. Norrima Mokhtar



She received the Bachelor of Engineering (B. Eng) degree in Electrical Engineering from University of Malaya in 2000. She was appointed as a lecturer to serve the Department of Electrical Engineering, University of Malaya immediately after graduating with her Master of Engineering. As part of her career development, she received SLAB/SLAI scholarship to attain her Ph.D. in 2012. She is now serving Department of Electrical Engineering, University of Malaya.
