

Lightweight Intelligent Recognition of Geo-Authenticity for Fangfeng Medicinal Materials Based on Improved ShuffleNet V2 Postprint

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Abstract

[Objective/Significance] Currently, methods for identifying the origin and quality of Fangfeng medicinal materials primarily rely on their physical or chemical characteristics. These methods require separation and extraction of the medicinal materials, which suffer from issues such as time-consuming processes, high costs, strong professional requirements, and high technical difficulty, making them unsuitable for widespread promotion and application. With the continuous development of deep learning, its advantages—including the elimination of manual feature extraction and high classification accuracy—have been widely applied in the identification of medicinal materials.

[Method] To address the problems of high computational load and low accuracy in most convolutional neural network models for identifying Fangfeng medicinal materials, this study proposes an improved lightweight geo-authenticity identification model for Fangfeng based on ShuffleNet V2. The model architecture is adjusted to reduce the number of parameters and computational load without compromising network performance. The Hourglass Residual Network is employed to replace the traditional residual network, while the SE (Squeeze-and-Excitation) attention mechanism is introduced. The hourglass residual network with additional channel attention is embedded into ShuffleNet V2, and the SiLU activation function is used to replace the ReLU activation function to enrich local feature learning, thereby proposing the lightweight traditional Chinese medicine Fangfeng geo-authenticity identification model Shuffle-Hourglass SE. To verify the effectiveness of the proposed model, four classic network models—VGG16, MobileNet V2, ShuffleNet V2, and SqueezeNet V2—are selected for comparative experiments.

[Results and Discussion] The results demonstrate that the Shuffle-Hourglass SE model proposed in this study achieves optimal performance. On the test set, it attains 95.32% accuracy, 95.28% recall, and an F1 score of 95.27%. The test time

and model size are 246.34 ms and 3.23 M, respectively. It is not only optimal among traditional CNN networks but also possesses significant advantages in lightweight networks.

[Conclusion] The model proposed in this study maintains high recognition accuracy while occupying less storage space, which will facilitate real-time diagnosis of Fangfeng geo-authenticity on low-performance terminals in the future.

Full Text

Lightweight Intelligent Recognition of *Saposhnikovia Divaricata* (Turcz.) Schischk Originality Based on Improved ShuffleNet V2

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Abstract

[Objective/Significance] *Saposhnikovia divaricata* (Turcz.) Schischk is a traditional Chinese medicinal herb. Current methods for identifying its origin and quality rely primarily on physical or chemical characteristics, requiring separation and extraction processes that are time-consuming, expensive, highly specialized, and technically demanding—limiting their widespread application. With the continuous development of deep learning, its advantages of automatic feature extraction and high classification accuracy have been widely applied to traditional Chinese medicine identification. [Methods] To address the problems of high computational cost and low accuracy in most convolutional neural network models for identifying *Saposhnikovia divaricata*, this study proposes an improved lightweight ShuffleNet V2-based model for originality recognition. The model architecture was adjusted to reduce parameters and computational complexity without degrading network performance. The traditional residual network was replaced with a hourglass residual network, while the Squeeze-and-Excitation (SE) attention mechanism was introduced to embed an additional channel-attention hourglass residual network into ShuffleNet V2. The SiLU activation function replaced the ReLU activation function to enrich local feature learning, resulting in a lightweight identification model called Shuffle-Hourglass SE. [Results and Discussion] Experimental results demonstrate that the proposed model achieved optimal performance, attaining 95.32% accuracy, 95.28% recall, and an F1-score of 95.27% on the test set. These metrics

represent improvements of 2.09%, 2.1%, and 2.19% respectively over the original ShuffleNet V2 model. The test time and model size were 246.34 ms and 3.23 MB, offering advantages over both traditional CNNs and other lightweight networks. [**Conclusion**] The proposed model maintains high recognition accuracy while occupying minimal storage space, facilitating future real-time diagnosis of *Saposhnikovia divaricata* originality on low-performance terminals.

Keywords: *Saposhnikovia divaricata* (Turcz.) Schischk; originality recognition; ShuffleNet V2; SE attention mechanism; hourglass residual network; traditional Chinese medicine; lightweight model

1. Introduction

Traditional Chinese medicine plays a crucial role in disease prevention and control. *Saposhnikovia divaricata* (Turcz.) Schischk, the dried root of the Umbelliferae plant, is slightly sweet, pungent, and warm in nature. As a renowned authentic medicinal material in Northeast China, it possesses diaphoretic, wind-dispelling, antispasmodic, and dampness-overcoming effects. Its genuine production areas are located at the intersection of Inner Mongolia, Jilin, Liaoning, and Heilongjiang provinces. Current identification methods for origin and quality primarily rely on physical or chemical characteristics, which cannot accurately measure the authenticity and quality superiority of *Saposhnikovia divaricata*.

Several studies have modeled and identified medicinal material originality. Zhang et al. employed the PEN3 electronic nose system to quantitatively characterize odors from different origins of *Marsdenia tenacissima* and its adulterants, establishing an authenticity and originality identification model with discriminant factor analysis validation achieving over 90% accuracy. Liu et al. utilized Fourier-transform infrared spectroscopy combined with discriminant analysis to study *Panax notoginseng* originality and origin, testing 136 samples from 13 cultivation sites across 11 counties, achieving 76.5% prediction accuracy. Zhang et al. applied chemometric methods to classify, differentiate, and model medicinal materials from various origins for traceability purposes. While these modern techniques address the subjectivity of traditional quality assessment and enable data-driven, objective identification with promising applications in distinguishing TCM originality, they require separation and extraction processes that suffer from long duration, high cost, specialization requirements, and technical complexity—limiting widespread adoption.

Deep learning algorithms have significantly improved recognition rates in traditional identification tasks, particularly convolutional neural networks (CNNs), which are rapidly becoming the preferred method for image recognition. Various CNN modifications have been proposed to achieve high accuracy and speed for visual tasks. Researchers have developed excellent networks including AlexNet, VGGNet, GoogLeNet, ResNet, and DenseNet, gradually applying them to plant disease severity identification. As deep learning continues evolving, its advan-

tages of automatic feature extraction and high classification accuracy have been widely adopted across domains, with increasing research introducing deep learning to traditional Chinese medicine identification—particularly for species and quality classification.

Zhao employed CNNs to extract features from appearance images of different *Lycium barbarum* origins, achieving 96% accuracy for online originality identification. Li et al. integrated a coordinate attention model with residual modules, achieving 97.23% accuracy for traditional Chinese medicine image recognition under transfer learning and data augmentation. Lyu collected images of 100 common traditional Chinese medicines using mainstream object detection models, with YOLOv5 demonstrating clear advantages at 94.33% average accuracy. Xing constructed a DenseNet model using PyTorch and Keras frameworks for various traditional Chinese medicine identification, achieving 97.5% maximum recognition rate with transfer learning. However, most CNNs possess large parameter counts and computational requirements due to their deep, complex architectures, making them dependent on powerful GPUs and difficult to deploy on portable devices with limited hardware resources—hindering convenient identification of medicinal material originality.

To address these limitations, researchers have proposed lightweight networks such as Xception, MobileNet, MobileNet V2, and ShuffleNet V2. Lightweight networks feature fewer parameters and lower memory requirements, achieving excellent balance between speed and accuracy for memory-constrained mobile devices. Lightweight network-based identification has become a research hotspot. Liu et al. fine-tuned MobileNet V2 pre-trained parameters multiple times for 12-category traditional Chinese medicine image recognition, achieving 93% validation accuracy while reducing training time by over $2\times$ compared to conventional CNNs.

This study addresses the challenges of complex spatial morphology and color texture features with low discriminability among *Saposhnikovia divaricata* from the same species. We propose an attention-embedded ShuffleNet V2-based network model (Shuffle-Hourglass SE) for *Saposhnikovia divaricata* originality identification, using self-captured images to construct and augment the dataset.

2.1 Depthwise Separable Convolution

To accelerate network computation and reduce computational cost, MobileNet proposed depthwise separable convolution. Traditional convolution employs $N\times N$ kernels, while depthwise separable convolution comprises depthwise convolution and pointwise convolution—equivalent to using channel-wise 1×1 kernels for separate convolution operations on each input channel. For an input image of size $H\times W$, where H and MN respectively.

As shown in Equation (1), the ratio of depthwise separable convolution computational cost to standard convolution is:

$$\frac{H \times W \times N \times K^2 + H \times W \times M \times N}{H \times W \times N \times K^2 \times M} = \frac{K^2}{N} + \frac{1}{K^2} \quad (1)$$

In ShuffleNet V2, M is much larger than K^2 , and depthwise convolution kernel size K is typically 3. Therefore, compared with standard convolution, both computational cost and parameter quantity can be significantly reduced to 1/8–1/9.

2.2 Model Network Structure Adjustment

To minimize parameter and computational consumption without affecting model performance, this study reduced the stacking quantities of Stage2, Stage3, and Stage4 in ShuffleNet V2 to one each. Following the initial 3×3 conventional convolution, a depthwise separable convolution with 24 channels, 3×3 kernel size, and stride 2 was employed to extract more effective and abundant features. The ShuffleNet V2 network structure is shown in Figure 1 [Figure 1: see original paper], and the internal parameters of the improved Shuffle-Hourglass SE model are presented in Table 1. In the table, Stages 2, 3, and 4 consist of basic units and downsampling units. When stride equals 2, downsampling units reduce output dimensions; when stride equals 1, basic units perform feature extraction without downsampling.

2.3 Hourglass Residual Network with Additional Channel Attention

ShuffleNet V2, MobileNet, Xception, and ResNet utilize channel shuffling and depthwise separable convolution to optimize ResNet's residual structure, ensuring network accuracy while improving computational efficiency. Unlike inverted residual blocks, hourglass residual networks can obtain more information from high-dimensional features and resolve gradient issues caused by shortcut connections. Using depthwise convolution, batch normalization, and activation functions, input feature maps are split into two branches X_1 and X_2 . X_2 undergoes depthwise separable convolution, two 1×1 convolutions, another depthwise separable convolution, followed by batch normalization, Sigmoid activation, and channel shuffle. Channel shuffle is then applied to mix deep and non-deep features.

The SE (Squeeze-and-Excitation) module structure is shown in Figure 2 [Figure 2: see original paper]. First, a feature map U with C channels and size $H \times W$ is flattened via global pooling F_{sq} into a $(1,1,C)$ feature vector, as shown in Equation (2):

$$Z_c = F_{sq}(u_c) = \sum_{j=1}^{H \times W} u_c(i, j) \quad (2)$$

where F_{sq} represents the squeeze operation, u_c is the feature map, and Z_c denotes the channel-wise attention.

The SE channel attention module is inserted after the depthwise separable convolution in the hourglass residual network to perform channel-dimensional feature extraction on its output. The hourglass residual network structure with additional channel attention is shown in Figure 3 [Figure 3: see original paper], and the channel shuffle process is illustrated in Figure 4 [Figure 4: see original paper].

2.4 SiLU Activation Function

Data imbalance exists among *Saposhnikovia divaricata* from different origins, with categories having fewer images prone to overfitting during training. The ReLU activation function in ShuffleNet V2 introduces sparsity to reduce unnecessary negative values and improve network generalization, as shown in Equation (3):

$$f(x) = \max(0, x) \quad (3)$$

where x is the activation function input and $\max()$ returns the maximum value.

The SiLU activation function retains ReLU's advantages while better addressing neuron death, with the expression shown in Equation (4):

$$f(x) = \frac{x}{1 + e^{-x}} \quad (4)$$

A comparison of ReLU and SiLU functions is shown in Figure 5 [Figure 5: see original paper]. Unlike ReLU, SiLU is smooth and non-monotonic. Replacing ReLU with SiLU in ShuffleNet V2's downsampling and basic units can improve overall model performance.

2.5 Improved ShuffleNet V2 Network Structure

Research indicates that inverted residual blocks project features to low-dimensional maps through intermediate expansion layers, causing channel compression that cannot retain sufficient useful information. The first and last convolutional layers in the hourglass residual block's main branch are spatial depthwise convolutional layers that preserve channels, enabling acquisition of more information from high-dimensional features. Drawing from hourglass residual concepts, this study introduces improved residual modules into ShuffleNet V2, replacing inverted residuals with hourglass residuals. The SE channel attention module is inserted after the depthwise separable convolution, embedding the hourglass residual network with additional channel attention into ShuffleNet V2. SE attention enhances important features and suppresses unimportant ones by controlling channel ratio sizes, making extracted features more directional. Replacing ReLU with SiLU in ShuffleNet V2's downsampling and basic units enhances model generalization while adjusting architecture

to reduce parameters and computation without degrading performance. The improved ShuffleNet V2 network structure—ShuffleNet-Hourglass SE—is shown in Figure 6 [Figure 6: see original paper].

3.1 Dataset Source and Preprocessing

Saposhnikovia divaricata samples used in this study were provided by the Traditional Chinese Medicine Laboratory of Jilin Agricultural University, comprising authentic samples from major production areas including over 1000 samples from five origins: Heilongjiang, Jilin, Hebei, Gansu, and Inner Mongolia. A total of 5234 images were captured indoors under white daylight using mobile phones, fully considering geographical distribution differences. The dataset was augmented to 10,120 images through random flipping, random cropping, brightness and contrast enhancement. The entire dataset was split with 80% for training and 20% for testing, as shown in Table 2. Sample dataset images are shown in Figure 7 [Figure 7: see original paper].

3.2 Experimental Settings

To ensure iteration efficiency and improve model stability and generalizability, input images were fixed at 224×224 pixels. The Adam optimizer was used with batch size 32, initial learning rate 0.001, and 50 training epochs. Experiments were conducted on a Linux system with an Intel Core i7-10900K CPU, 32 GB DDR4 RAM, CUDA 11.4, and PyTorch 3.9 deep learning framework.

3.3 Model Evaluation Metrics

Network performance was evaluated using accuracy, precision, recall, and F1-score, calculated as shown in Equations (5)–(8). Model complexity was compared based on parameter count and average single-image inference time.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (5)$$

$$Precision = \frac{TP}{TP + FP} \times 100\% \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \times 100\% \quad (7)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100\% \quad (8)$$

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

3.4.1 Comparative Experiments with Different Models

To evaluate the proposed model's effectiveness, VGG16, MobileNet V2, ShuffleNet V2, and SqueezeNet V2 were selected for comparison. All five models used the proposed dataset and identical training parameters. Performance was evaluated using loss, accuracy, recall, and F1-score on both test and training sets, with results shown in Figures 8 [Figure 8: see original paper] and 9 [Figure 9: see original paper].

The Shuffle-Hourglass SE model achieved lower loss values and higher accuracy, with training and test set losses of 0.075 and 0.122 respectively. The model converged faster than ShuffleNet V2, stabilizing around 20 epochs. Comparative results on the test set are presented in Table 3 .

The Shuffle-Hourglass SE model achieved optimal performance with 95.32% accuracy, 95.28% recall, and 95.27% F1-score—improvements of 2.09%, 2.1%, and 2.19% over ShuffleNet V2 respectively. Test time and model size were 246.34 ms and 3.23 MB, offering advantages over both traditional CNNs and lightweight networks. Compared with VGG16, the proposed model improved accuracy by 7.41%, reduced test time by 71.89%, and decreased model size by 96.76%. Although ShuffleNet V2 and MobileNet V2 had similar test times, the improved Shuffle-Hourglass SE model demonstrated superior accuracy and speed, reducing test time by 69.31 ms and model size by 1.98 MB while improving accuracy by 10.5% compared to MobileNet V2. The improved network maintains high recognition accuracy and classification performance, showing improvements over the unmodified ShuffleNet and significant enhancements over other lightweight networks.

3.4.2 Effects of Different Attention Mechanisms

To validate the effectiveness of the proposed SE attention mechanism in the hourglass residual network with additional channel attention, comparisons were made with ECA (Efficient Channel Attention), CBAM (Convolutional Block Attention Module), and CA attention mechanisms. All attention mechanisms were introduced at identical positions in the ShuffleNet V2 model, with results shown in Table 4 .

Compared with ECA, the SE attention mechanism achieved higher accuracy and F1-score, enabling better channel information interaction. Compared with CA, SE improved accuracy and F1-score by 0.68% and 0.82% respectively while reducing parameters by 0.51 MB. Compared with CBAM, SE improved accuracy and F1-score by 1.19% and 1.38% respectively without parameter increase. Thus, the proposed SE attention mechanism achieves superior accuracy and F1-score with optimal parameter efficiency.

3.4.3 Effects of Different Activation Functions

Replacing ReLU with SiLU in ShuffleNet V2's downsampling and basic units enhances model generalization. To verify effectiveness, ReLU, H-swish, and ELU activation functions were compared under identical parameters, with results shown in Table 5 .

The ELU activation function performed poorly compared to ReLU. H-Swish slightly improved accuracy and F1-score. SiLU achieved the best results with 95.32% accuracy, improving accuracy and F1-score by 2.09% and 1.93% respectively.

3.4.4 Ablation Study Results

To investigate performance improvements from the SE attention mechanism, hourglass residual block, and activation function modifications, ablation studies were conducted on the Shuffle-Hourglass SE model, with results shown in Table 6 .

Adding SE attention to ShuffleNet V2 improved accuracy by 1.3%. Introducing hourglass residual modules improved accuracy by 0.89% but increased parameters significantly. Replacing ReLU with SiLU improved overall accuracy by 1.21%. Architecture adjustments substantially reduced parameters and computation. The final Shuffle-Hourglass SE model achieved 95.32% accuracy with 3.23 MB parameters—2.09% higher accuracy and 1.29 MB fewer parameters than the original ShuffleNet V2.

5. Conclusion

Addressing the challenges of complex spatial morphology and color texture features with low discriminability among *Saposhnikovia divaricata* from the same species, this study proposes an attention-embedded ShuffleNet V2-based network (Shuffle-Hourglass SE) for originality identification using self-captured and augmented *Saposhnikovia divaricata* images.

1. Using ShuffleNet V2 as the base architecture, traditional residuals were replaced with hourglass residuals while introducing SE attention mechanisms. The hourglass residual network with additional channel attention was embedded into ShuffleNet V2 to enrich local feature learning for different origins, optimizing the originality identification model. SiLU activation functions replaced ReLU, further improving ShuffleNet V2 performance.
2. The improved Shuffle-Hourglass SE model achieved 95.32% accuracy on the self-constructed dataset with only 3.23 MB model size. Compared with the unmodified ShuffleNet V2, accuracy and F1-score improved by 1.69% and 1.23% respectively while model size decreased by 96.76%. Although Li et al. achieved 97.23% accuracy using an improved DenseNet for *Saposhnikovia divaricata* originality identification—1.91% higher than

our model—the proposed model demonstrates superior performance in parameters, test time, and model size.

The proposed model maintains high recognition accuracy with minimal storage space, offering advantages in test time and high portability, facilitating future real-time diagnosis of *Saposhnikovia divaricata* originality on low-performance terminals.

Conflict of Interest Statement: The authors declare no conflicts of interest regarding this research or its publication.

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