



Classification of Images on three *Fritillaria cirrhosa* species using deep learning

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Abstract: *Fritillaria cirrhosa* has powerful therapeutic characteristics that can help treat pulmonary diseases. For thousands of years, the *Fritillaria cirrhosa* species has been utilized in traditional Chinese medicine. Deep residual convolutional neural networks were used to directly input the unprocessed raw image, and the characteristics of the image were retrieved via convolution and pooling. We used the classifier to classify the three *Fritillaria cirrhosa* species. We use the Inception v3 architecture to differentiate between images of three different species of *Fritillaria cirrhosa*. We are training the model to recognize the species of *Fritillaria cirrhosa* with a dataset of 3915 photos, while the validation dataset is 480. The ultimate recognition accuracy rate for the training set was 96.5%, the validation set was 96.04%, and the test set was 91.4%. Finally, our research results indicate that deep learning, specifically the Inception v3 architecture, is effective at accurately recognizing *Fritillaria cirrhosa* species.

Index Terms: *Fritillaria cirrhosa*, Deep Learning, Convolutional neural networks, Inception v3.

1. Introduction

Fritillaria cirrhosa, a traditional Chinese medicine with a long medical history, has multiple functions: eliminating heat and moistening the lung, alleviating cough and reducing sputum, resolving carbuncles, and expelling boils. It is described as a medium-grade herb in the “Shennong’s Classic of Material Medical” and is known as a “holy medicine for relieving cough”[10].

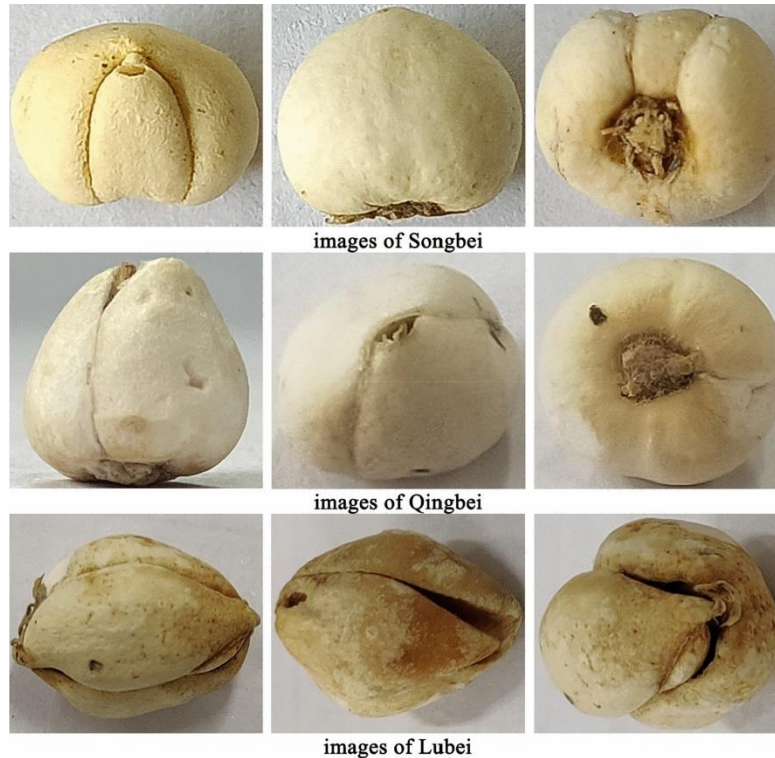
It is derived from the dried Bulbs of the genus *Fritillaria* (Liliaceae), such as *Fritillaria unibracteata* Hsiao et K. C. Hsia, *Fritillaria cirrhosa* D. Don, *Fritillaria przewalskii* Maxim., *Fritillaria delavayi* Franch., *Fritillaria taipaiensis* P. Y. Li, and *Fritillaria unibracteata* Hsiao et K. C. Hsia var. *Wabuensis* (S. Y. Tanget S. C. Yue) Z. D. Liu, S. Wang et S. C. Chen[8]. The quality of *Fritillaria cirrhosa* can be classified as Songbei, Qingbei, Lubei, or grown items based on their various features, ranging from high to low.

There are about 200 types of Chinese patent drugs made with *Fritillaria cirrhosa* as the primary raw material, and the market demand is tremendous. Furthermore, *Fritillaria cirrhosa* growth circumstances are hard, and excessive harvesting has severely depleted

its resources, resulting in a steady price rise (Cunningham, A. B. et al. High-altitude species yield high profits: Is it possible to trade wild harvested *Fritillaria cirrhosa* (Liliaceae)[5]).

Songbei has the highest price, followed by Qingbei, and Lubei has the lowest, resulting in inferior products being offered as better on the market. Apart from the price, the therapeutic effects of different *Fritillaria*

cirrhusa vary slightly. As a result, correctly identifying *Fritillaria cirrhosa* is important not only for consumer economic interests but also for the quality and therapeutic efficacy of Chinese cut crude drugs [12].



Examples of Songbei, Qingbei, and Lubei.

2. Literature Review

An, Y. L., Wei, W. L., and Guo, D. A. Application of analytical technologies in the discrimination and authentication of herbs from *Fritillaria* [1]. Empirical identification approach, judgment based on appearance features, such as the shape, color, and size of *Fritillaria cirrhosa*.

This method is simple to use, but it takes a large staff, and the identifier requires special training to get considerable knowledge in pharmaceutical identification. Individual variances exist, and sensory sensitivity, subjectivity, weariness, and other factors can all have an impact on recognition outcomes.

Physicochemical methods for identifying *Fritillaria cirrhosa* based on its chemical composition consist of thin-layer chromatography [9], spectrophotometry [2], thermogravimetric analysis [7], high-performance liquid chromatography [6], fluorescence

spectrometry [3], electrospray mass spectrometry [13], electron tongue and electron nose [14].

[11][15] Protein mapping analysis, DNA labeling, and molecular probe technology are biological methods for classifying *Fritillaria cirrhosa* based on its distinctive proteins or DNA. This approach is extremely sensitive and specific, but it demands advanced analytical equipment and an atmosphere for operation.

Hu, K. et al. 2019 IEEE 4th International Conference on Image, Vision, and Computing [16]. Image processing and pattern recognition approach, which employs computer technology and mathematical methodologies to process and analyze images of *Fritillaria cirrhosa* and classify them according to features.

Wang, Y., Li, Y., and Li, D. Recognizing traditional Chinese medicine *poria* microscopic pictures based on texture [17]. Image processing is an important way to automate the identification of *Fritillaria cirrhosa*. Wang et al. acquired eight features, including multi-scale wavelets and fractal dimension, and used discriminant analysis to automatically identify *Fritillaria cirrhosa* powder micrographs.

Liu et al. [19] proposed a multi-scale wavelet transform-based edge detection approach for reliably and effectively retrieving target information edges in *Fritillaria cirrhosa* micrographs, followed by automatic *Fritillaria cirrhosa* categorization. Liu et al. [19] used transfer learning to train a model that was then combined with the EfficientDet-B0 target detection network and the k-means clustering approach to automatically identify three species of *Fritillaria cirrhosa*. These methods not only involve the use of image segmentation algorithms to aid in the localization of *Fritillaria cirrhosa*, but they also necessitate the manual construction of important extraction features, which makes it difficult to meet the requirements of rapid automatic recognition.

There have been a few studies that use deep learning methods to identify *Fritillaria cirrhosa*. Hu et al. [16] classified the *Fritillaria cirrhosa* dataset using the deep learning framework SE-DPU, but did not offer recognition accuracy or related misjudgment results, nor did they characterize the neural network's structure and key parameters.

3. Dataset Description

In this study, three commercial specifications of *Fritillaria cirrhosa*, a traditional Chinese medication, were chosen as research subjects. Professor Ribao Zhou of the Hunan University of Chinese Medicine classified the samples as Songbei, Qingbei, and Lubei respectively [4]. To make the experimental images more representative of the market's natural circulation state and reflect the randomness of the sample selection process, various photographers, light intensities, shooting equipment (ordinary smartphones), and shooting angles were used to collect images of *Fritillaria cirrhosa*.

A total of 3915 images of *Fritillaria cirrhosa* were collected, including 1305 images of Songbei, 1305 images of Qingbei, and 1305 images of Lubei for training purposes. For the validation dataset, 480 images of *Fritillaria cirrhosa* were used, consisting of 160 images of Songbei, 160 of Qingbei, and 160 of Lubei. For the Testing dataset, there are 480 images

of *Fritillaria cirrhosa*, with 160 images of Songbei, 160 of Qingbei, and 160 of Lubei.

Model Name	Training Set	Validation Set	Testing Set	Total
Songbei	1305	160	160	1625
Qingbei	1305	160	160	1625
Lubei	1305	160	160	1625
Total	3915	480	480	

4. Deep Learning using Inception v3

This study presented an automatic classification of *Fritillaria cirrhosa* images using an Inception v3 deep convolutional neural network. Inception v3 is a deep convolutional neural network architecture that is widely utilized for image recognition as well as classification tasks. Inception v3 aims to enhance accuracy and efficiency in the classification of images.

Inputting an image of *Fritillaria cirrhosa*, processing it with the upgraded Inception v3 deep convolutional neural network, and finally displaying the *Fritillaria cirrhosa* species.

The Inception V3 model consists of 42 layers, including a Conv 3x3 convolution layer. Each block contains convolution, average pooling, batch normalization, and an activation function. The Softmax classifier was applied to classify the three output categories.

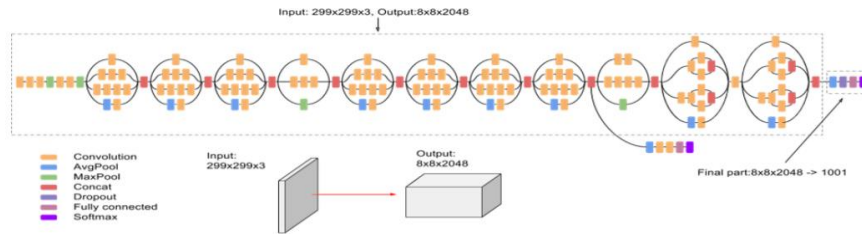


Fig 2: Basic Structure of Inception v3 in Deep Learning

4.1. Convolutional Layer

In Inception v3, the “Conv” (convolutional) layers are the essential building blocks that extract information from input pictures. Inception v3 Conv layers are crucial for representation learning, allowing the network to recognize meaningful spatial patterns and structures in input images. These layers serve as the network’s backbone, allowing the model to perform classification and prediction tasks more efficiently.

4.2 Batch Normalization

Batch normalization helps mitigate the vanishing or inflating gradient problem by ensuring that the activations within each layer remain within a specific range. By normalizing the inputs to each layer, batch normalization prevents gradients from becoming excessively high or too tiny, which can impede training or cause numerical instability.

This enhances gradient flow through the network, resulting in more efficient training and faster convergence. Batch normalization is essential for training deep neural networks such as Inception v3 because it stabilizes the training process, reduces overfitting, improves

gradient flow, and allows for the use of greater learning rates. It is a critical component for getting top-tier performance in image recognition and other deep-learning applications.

Let x be the input to the batch normalization layer, μ be the mean, σ^2 be the variance, γ be the scale parameter, β be the shift parameter, ϵ be a small constant for numerical stability, $\text{BN}(x)$ represent the batch normalization operation, and $\text{BN}(x; \mu, \Sigma)$ denote batch normalization with precomputed mean and variance.

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2$$

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv \text{BN}_{\gamma, \beta}(x_i)$$

4.3 Activation Function

Inception v3 relies heavily on the ReLU (Rectified Linear Unit) activation function to introduce non-linearity, promote sparsity, and mitigate difficulties such as vanishing gradients. It creates non-linearity in the network

by zeroing away negative activations while keeping positive activations unaltered. The mathematical expression for ReLU is:

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

Its simplicity, efficiency, and effectiveness make it a popular choice for convolutional neural networks, which helps models like Inception v3 succeed in a variety of image recognition tasks.

4.4 Softmax Classifier

Inception v3 relies heavily on the softmax classifier to convert the network's raw output logits into class probabilities, allowing the model to generate probabilistic predictions about the content of incoming images.

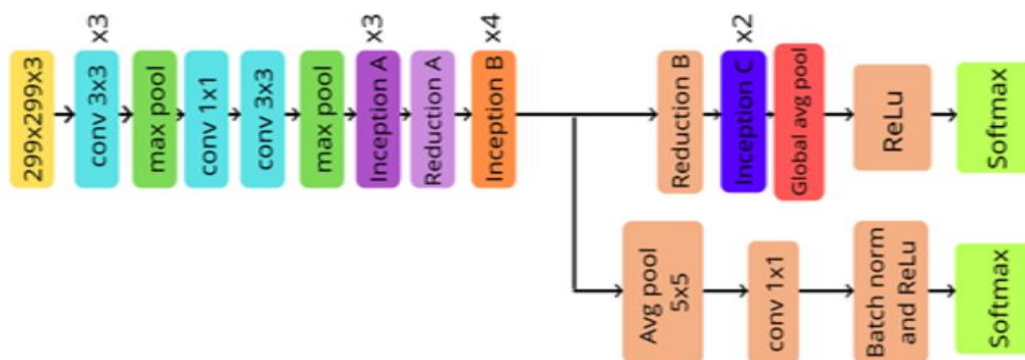


Fig 3: Architecture Layer of Inception V3 for *Fritillaria cirrhosa*

5. Training Process

This paper examines the training procedure for the Inception v3 convolutional neural network model. Inception v3 makes use of several convolutional modules, including the inception modules, which are composed of concurrent convolutional procedures with varying kernel sizes. This enables the network to successfully capture features at diverse spatial scales, resulting in increased recognition performance for objects of varying sizes and complexities. Inception v3 uses dimensionality reduction techniques such as 1x1 convolutions followed by max pooling to minimize the network's computational cost and memory footprint while retaining critical spatial information. This helps to increase efficiency without losing performance. Inception v3 uses factorized convolutions to minimize the number of parameters and computational complexity of the network, making it more efficient and easier to train. Batch normalization mitigates concerns like vanishing gradients while also improving the network's general stability and speed. The model had been trained with 250 epochs.

6. Model Recognition Results

The trained Inception v3 deep network model was used to test the recognition of 480 images of three types of *Fritillaria cirrhosa*: Songbei, Qingbei, and Lubei in the validation set, with accuracy results of 96.04% and 91.4% in the test set, respectively.

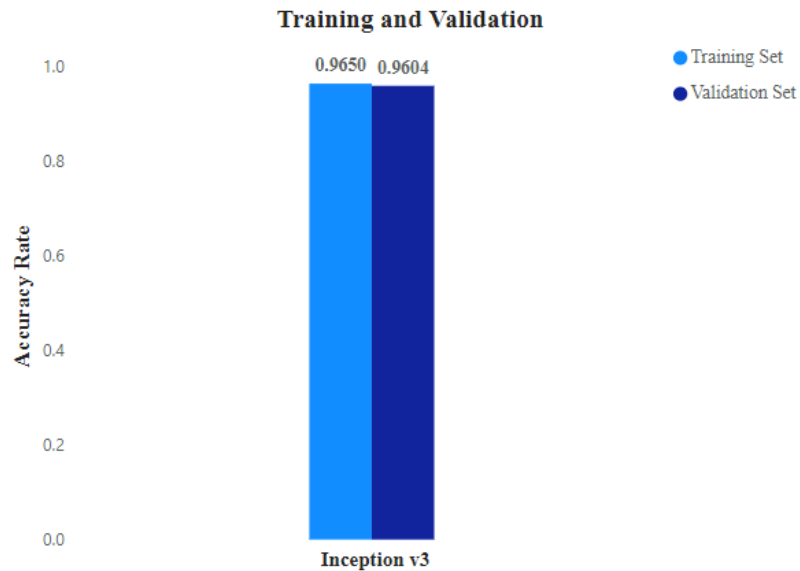


Fig 4: Experimental Results of Inception v3

7. Comparison of Deep Learning Model

[4]To test the viability of the upgraded ResNet34 network model suggested in this paper, it was compared to the classical ResNet18, Alexnet, and VGG16 models in deep learning using the same computer environment. The upgraded ResNet34 demonstrated the highest recognition accuracy on both the training and validation sets, which was greater than 90%. ResNet18 had the second-greatest recognition accuracy, while VGG16 had the lowest at 33.3%.

However, Inception v3 outperforms other deep learning models. The recognition accuracy percentage for both training and validation is greater than 94%. Inception V3 has the highest recognition rate when compared to ResNet 34, ResNet 18, AlexNet, and VGG16

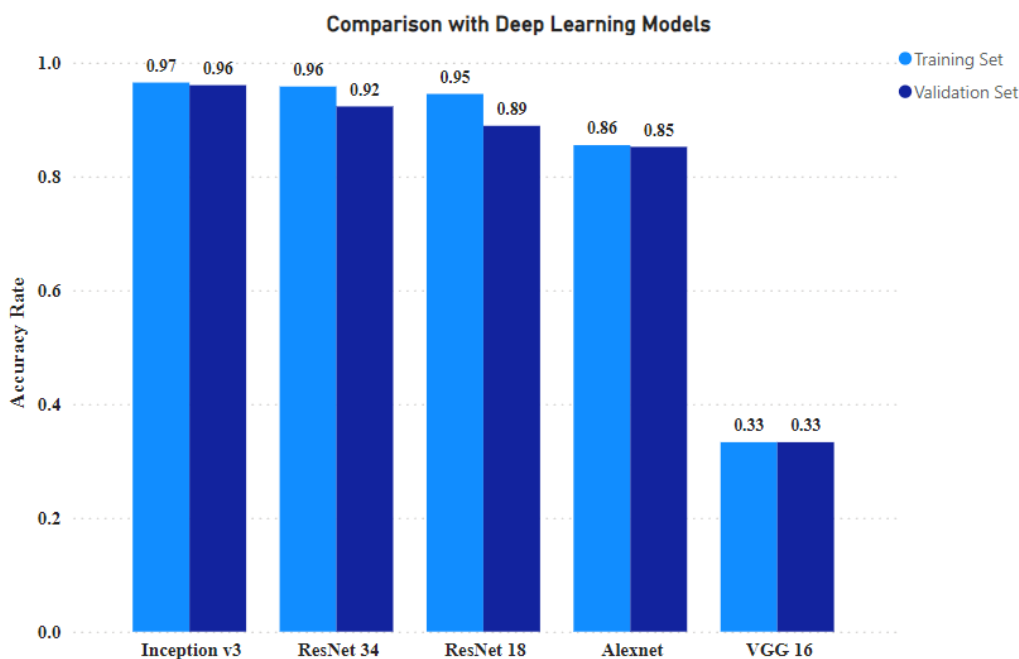


Fig 5: Results of Comparison of Different Deep Learning Models with Inception v3

8. Conclusion

This study used deep learning approaches to conduct classification and recognition research on images of three types of *Fritillaria cirrhosa* on the market, including Songbei, Qingbei, and Lubei, by developing a residual convolutional neural network model. The primary conclusions were as follows:

- This study took advantage of the benefits of deep residual convolutional neural networks, which can automatically extract picture characteristics, avoiding the influence of human subjectivity induced by manual feature extraction and omitting individual differences. Furthermore, its network structure was well suited to processing vast amounts of sample data with high recognition accuracy.
- A comparison analysis of classical deep learning models (ResNet34, ResNet18, Alexnet, and VGG16) was undertaken in the same computing environment to ensure accuracy of this approach. This method's recognition accuracy was 96.04%, well exceeding that of ResNet 34 (92.3%), ResNet18 (88.9%), Alexnet (85.2%), and VGG16 (33.3%). This research technique was both practical and effective.

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