REMOTE SENSING PLANT IMAGE RECOGNITION AND LANDSCAPE ENVIRONMENT DESIGN BASED ON IMPROVED DEEP LEARNING MODEL

CONG, R. J.[1] – HE, Y.[1*] – HUANG, S.[2]

[1]*College of Art and Design, Guangdong University of Science and Technology, DongGuan 523000, China*

[2]*Department of Plastic Arts, Wonkwang University, Iksan-si, Jeollabuk-do 54538, South Korea*

[*]*Corresponding author*
e-mail: heyi921125@163.com

(Received 9th Jul 2024; accepted 18th Dec 2024)

Abstract. Landscape environment design is often faced with complex remote sensing plant image recognitionproblems. The research aims to improve the recognition accuracy and efficiency of plant remote sensing images, especially in landscape environment design and ecological monitoring applications, and proposes an improved ResNet50 model for image recognition. This method optimizes the performance of remote sensing plant image recognition by lightweight design of ResNet50 model and introducing EfficientNet network. The research aims to address the limitations of traditional manual feature recognition methods in processing complex plant remote sensing images, and improve the accuracy and robustness of image recognition. Results showed that the model was observed to learn rapidly at first and decreased in the later learning stage, and finally obtained the best accuracy of 99.78% around the 10th epoch. The model achieved an accuracy of 88.5% after 600 epochs, showing better performance. Through iterative training, the best recognition results showed that the average accuracy of the test set was 91.6%, and the F1 value was 0.92. The evaluation indicators in decision traceability and model comprehension reached 94% and 95%, respectively. While ensuring performance, the model also had high computational efficiency, with an average training time of 94.28 seconds and an average prediction time of 95.16 seconds. The proposed model has successfully improved the accuracy and efficiency of remote sensing plant image recognition, providing powerful tools for the field of landscape design and making important contributions to promoting the development of landscape environmental design.
Keywords: *improved ResNet50, plant recognition, remote sensing technology, ecological monitoring, data-driven decision*

Introduction

Remote sensing image recognition has important applications in landscape environment design, providing high-resolution spatial and environmental information to assist designers in scientific planning and efficient management (Liu et al., 2021; Wang and He, 2023). Remote sensing images can accurately identify and classify vegetation types and distribution within landscape areas, providing designers with detailed data on the location and coverage range of different plant species, which is particularly important for optimizing ecological layout and improving greening effects (El-Ghany et al., 2020; Sun et al., 2021). In addition, remote sensing technology also supports long-term monitoring of plant growth and health levels, helping to evaluate the overall condition and trend of ecosystem changes, thereby providing guidance for landscape maintenance and management. Landscape environmental design is a multidisciplinary field that aims to create functional, aesthetic and sustainable Spaces through the planning and design of natural and man-made environments. It focuses not only on visual aesthetics, but also on ecological health, social needs and adaptability to physical conditions. In this process, the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

application of remote sensing plant image recognition technology is particularly important, because it can provide accurate information about plant species, distribution and growth state. These data provide a scientific basis for landscape architects in environmental analysis and planning, and help them develop targeted design schemes to optimize the layout of green space, so as to enhance the functionality and beauty of the overall environment. In addition, the technology can provide early warning of plant health conditions, thereby supporting ecological restoration and conservation efforts. Therefore, remote sensing plant image recognition plays a central role in landscape environment design and provides a strong support for achieving sustainable development goals. However, landscape environment design often faces complex remote sensing plant image recognition, and traditional remote sensing plant image recognition methods are usually based on manually formulated features and rules (Lauguico et al., 2020; Kattenborn et al., 2021; Sun et al., 2021). These methods have limited performance in processing complex plant remote sensing images and cannot meet the high requirements for accuracy and robustness (Kattenborn et al., 2020; Reddy, 2021; Yu and Li, 2024). Deep learning algorithms have developed rapidly in the past decade, especially with neural networks such as ResNet50 becoming the mainstream method for image recognition, providing new possibilities for solving the problem of remote sensing plant image recognition (Song et al., 2020; Yao et al., 2021). However, the traditional ResNet50 model has a large volume, a large number of parameters and calculations, which leads to certain limitations in its practical application (Morad et al., 2021; Wang et al., 2021). Therefore, the study first conducted a lightweight design on it and introduced the EfficientNet network on this basis to improve its performance in remote sensing plant image recognition. The purpose of this study is to optimize the model architecture and improve the accuracy and efficiency of recognition by making full use of large-scale plant image data sets. Specific goals include accurate identification of plant species and states under a variety of environmental conditions, while reducing computing resource requirements. It is hypothesized that the proposed method will be significantly superior to traditional image recognition techniques in processing complex plant remote sensing images, so as to provide more reliable data support for landscape environment design and ecological monitoring.

The main innovation of this study lies in the lightweight design of the ResNet50 model and the introduction of EfficientNet network on this basis. The EfficientNet network systematically balances and optimizes the depth, width, and resolution dimensions of the network through a composite scaling method, thereby significantly reducing computational complexity while maintaining model accuracy, and improving the adaptability of the model in different computing resource environments. The efficient characteristics of EfficientNet enable rapid and accurate identification of plant species when processing large-scale, high-resolution remote sensing images, thereby promoting the scientific and aesthetic aspects of landscape design. In addition, the improved model can adapt to the unique complexity and diversity of remote sensing images, significantly improving recognition performance and application breadth. Finally, the study applies the model to remote sensing plant image recognition and landscape environment design. By improving the ResNet50 model, it can adapt to the characteristics of plant remote sensing images and improve recognition performance. This automated and intelligent approach not only improves data processing capabilities, but also opens up new possibilities for real-time decision support in ecodesign. Through the combination of big data analytics and model learning, this framework can respond to rapidly changing environmental needs

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

and promote more scientific ecological planning and management, thereby having a profound impact in key areas such as sustainable development and biodiversity conservation. This innovative application demonstrates how AI can transform traditional environmental management approaches to achieve intelligent, precise and efficient ecological governance.

The contribution of the research is that by lightweight design of the ResNet50 model and introducing EfficientNet network, the accuracy and efficiency of remote sensing plant image recognition can be significantly improved, and it is suitable for the diversity and high resolution of complex images. Its specific advantage lies in the fact that the introduced EfficientNet can quickly and accurately identify plant species when processing large-scale, high-resolution remote sensing images, which contributes to the rationality and aesthetics of plant layout in landscape design.

The research will be carried out in five sections, the section 1 is introduction, the section 2 is an overview of the research on plant RSI recognition and landscape environment design based on the improved ResNet50, the section 3 is the research on plant RSI recognition and landscape environment design based on the improved ResNet50, the section 4 verifies the design, and the last section summarizes the research and shortcomings.

Related works

RSI recognition technology has been widely used in the fields of geographic information science, ecology, agriculture and climate change research, especially in plant RSI recognition, and its accuracy and efficiency are of great significance for the decision-making of landscape environment design. Wang (2021) emphasized the importance of analyzing urban landscape change and utilizing big data analysis to address environmental issues and enhance urban construction and ecological development. This study employed big data analysis techniques to analyze image characteristics captured by remote sensing sensors, offering valuable insights for urban landscape planning and environmental preservation (Wang et al., 2021). Shan and Sun (2021) designed a new system using virtual reality technology to solve the problem of traditional landscape planning effect simulation. By integrating green space gardens, parametric plant modeling was applied to achieve virtual construction and visualization of three-dimensional landscapes. The outcomes revealed a clear and high-quality design effect of the system. It received high scores in courtyard landscape and garden landscape design, while maintaining low application costs, energy consumption, and high operational efficiency (Shan and Sun, 2021). Hu and Gong (2021) developed a model system for urban landscape information mapping using RSI technology and a geographic information system (GIS) platform. The outcomes yielded a comprehensive summary of geological information mapping methods and urban landscape information mapping. Furthermore, this study established the objectives and content for future research on urban landscape information mapping (Hu and Gong, 2021). Lyu et al. (2021) extracted alteration information of two hydrothermal solutions associated with hydroxide and iron staining in the study area by principal component analysis based on the Crosta technique. The results showed that WV-2 imagery was able to accurately identify the mineralized geological body. The overall classification accuracy of boulder mapping based on SAM and SVM was 80.18% and 83.51%, respectively. Through field investigations, the information on the anomaly of ferrous hydroxyl staining was well matched to the actual

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

alteration region (Lyu et al., 2021). Pan et al. (2021) introduced in detail the sensor principle, design process, and technical issues, and summarized their advantages and disadvantages by discussing in depth most of the wireless passive SAW methods used in gas sensors. The study found that although the sensors were successfully applied to temperature or pressure monitoring in harsh environments, their application in chemical gases was reported less. A review of the current state of wireless passive SAW sensors for gas detection led to the proposal of new and promising prospects for related technology (Pan et al., 2021).

As a classic model in deep learning, ResNet50 is widely used in a variety of image recognition tasks due to its excellent performance and design ideas learning depth residuals. Wei et al. (2022) proposed RAG-Net, an effective iris segmentation method based on deep learning. By introducing the attention gate mechanism and the ResNet-50 module, the method achieved efficient iris segmentation in a non-cooperative environment. Experimental results showed that RAG-Net had high effectiveness in iris segmentation (Wei et al., 2022). Hu et al. (2021) proposed an EI-based generative data augmentation system, and experiments showed that the proposed generative data augmentation model E-DCGAN outperformed the baseline model in image generation and data augmentation in the agricultural and medical fields, with a reduction of 4.73% and 19.59% in FID values, respectively, and an improvement of 0.96% and 1.27% in the average accuracy of agricultural and medical classification results, respectively (Hu et al., 2021). Liao et al. (2021) used deep neural networks, such as ShuffleNet, GoogLeNet, ResNet18, ResNet50, VGG16, and DenseNet201, to classify machine tool turning operations by transfer learning methods. Four time-frequency analysis methods were discussed, emphasizing the multi-resolution capability of continuous wavelet transform. The VGG16 network achieved the highest classification accuracy of 92.67%, showing the potential for monitoring performance. By modifying the VGG-16 network and removing two convolutional layers to alleviate the overfitting problem, the classification accuracy was improved to 95.58% (Liao et al., 2021). Du et al. (2021) proposed a goal-oriented shallow and deep feature detection algorithm, which ensured that the network correctly processed small target instances by designing anchors suitable for small targets. Experimental results showed that the proposed algorithm correctly detected point targets when the local signal-to-noise ratio was about 1.3, which had great advantages and potentials (Du et al., 2021). Fu et al. (2022) developed a unified deep multi-view learning network, combining semantic content and image distortion for NR-IQA. Using ResNet50 as the backbone, the study designed semantic features of image quality assessment perception, rather than directly using a neural network model designed for image quality assessment as was the case with many existing methods. Then, a unified deep multi-view learning network was proposed, which combined semantic content and image distortion for NR-IQA (Fu et al., 2022). Abdel-Basset et al. (2020) proposed a completely unsupervised cross modal hierarchical clustering and refinement method to solve the problem of visible infrared personnel re identification. The research results indicate that unsupervised cross modal hierarchical clustering and refinement methods do not require manual annotation, surpassing the performance of multiple supervised methods (Abdel-Basset et al., 2020). Tesfamikael et al. (2021) proposed a unified unsupervised learning framework - camera invariant feature learning, to address the issue of camera differences in completely unsupervised personnel re identification. The research results validated the effectiveness of unsupervised learning frameworks on four ReID datasets, surpassing existing methods (Tesfamikael et al., 2021). Dhanachandra and Chanu (2020) proposed

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

an unsupervised VI ReID modal invariance modeling and refinement framework to address the issues of difficult sample influence and label noise. Research has shown that MIMR performs better than advanced unsupervised methods (Dhanachandra and Chanu, 2020).

In summary, current research has made some progress in the field of remote sensing plant image recognition by applying the Lightweight ResNet50+EffiUentNet. However, in the application of landscape environment design, there are still problems with low data processing efficiency and accuracy. To this end, research combines more efficient algorithm optimization and data augmentation techniques to improve model performance. In order to more effectively integrate interdisciplinary knowledge and promote the deep integration of remote sensing technology and landscape design.

Plant RSI recognition and landscape environment design method based on improved ResNet50

A plant RSI recognition algorithm using deep learning is constructed to effectively extract and transform complex image features. Secondly, the improved ResNet50 algorithm is implemented and optimized. Finally, a RSI feature extraction and classification model based on the improved ResNet50 is constructed to achieve accurate feature extraction and optimal classification of plant RSIs. It is expected to provide a new basis for the further development of RSI recognition technology and bring a new perspective to landscape environment design.

Construction and optimization of remote sensing plant image recognition algorithm based on Res Net50 algorithm

The interweaving of different geographical features, climate conditions, and vegetation types in landscape environments makes the types, forms, and distribution of plants in remote sensing images complex and variable. In addition, factors such as noise, occlusion, and lighting changes in the image further increase the difficulty of recognition. Artificial intelligence is particularly good at automatically learning and extracting features from large amounts of data, and can efficiently handle recognition tasks involving complex patterns and high-dimensional data. Deep learning is a sub-field of artificial intelligence that focuses on using neural networks, especially deep neural networks, to automatically learn and extract features from data to solve complex tasks. While AI is broader in scope, encompassing machine learning, natural language processing, computer vision, and expert systems, deep learning focuses on learning from large-scale data, enabling models to make pattern recognition and decisions. ResNet50, as an excellent deep learning model, has shown excellent performance in the field of image processing, especially in image classification and object detection tasks, and has achieved significant results. However, in the task of remote sensing plant image recognition, the ResNet50 model still has some undeniable limitations, such as its large model volume, large parameter and computational complexity, which leads to low computational efficiency. Therefore, in order to address the drawbacks of the ResNet50 skeleton network, which has high complexity, a large number of parameters, and requires a high parameter cost for expansion, the research first focuses on lightweight design. Firstly, the 64*64*256 of the first residual block in the traditional ResNet50 network is changed to 32*32*256 to reduce the model's parameter and computational complexity. Subsequently, the second convolutional layer in the ResNet50 network was adjusted to a

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

convolutional layer with 2*3*3 convolutional kernels. Finally, select the maximum pooling layer with a pooling size of 3*3. The structure of ResNet50 after lightweight is shown in *Figure 1*.

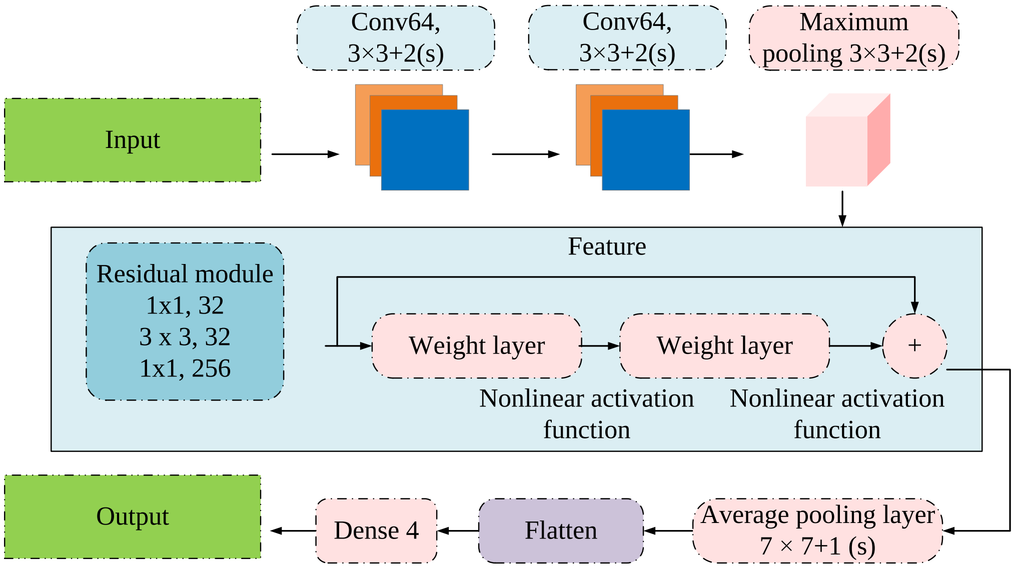

Figure 1. *Structure of ResNet50 after lightweight*

In *Figure 1*, The ResNet50 model extracts and stores features by processing input plant remote sensing image data. It learns through neural networks and finally achieves image recognition through output layers. Among them, the convolutional layer is an important component of the entire model, responsible for extracting local features of the image; The pooling layer reduces the data dimension to reduce computational complexity; The fully connected layer fuses the learned features to produce the final recognition result. The convolution operation is the core operation part of lightweight ResNet50, and its calculation formula is shown in *Equation (1)*.

$$(I,K)(x,y)=\sum_{i=0}^{k-1}\sum_{j=0}^{k-1}I(x+i,y+j)\times K(i,j) \quad \text{(Eq.1)}$$

In equation (1), I represents the input image matrix; K represent convolutional kernels; (x,y) indicates the output position; k indicates the size of the convolution kernel. The maximum pooling layer reduces the size of the input feature map while retaining important features, and its function expression is shown in *Equation (2)*.

$$P(x,y)=\max_{0\le i<k,0\le j<k} I(x+i,y+j) \quad \text{(Eq.2)}$$

In *Equation (2)*, P represents the output matrix after pooling. In the backpropagation algorithm, the model parameters are updated using the gradient descent method, as shown in *Equation (3)*.

$$\theta_{t+1}=\theta_t-\eta\Delta_\theta J(\theta) \quad \text{(Eq.3)}$$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

In *Equation (3)*, θ_t represents the model parameters at the t-th iteration; θ_{t+1} represents the model parameters at the $t+1$-th iteration; η indicates learning rate; $J(\theta)$ represent the loss function; $\Delta_\theta J(\theta)$ indicates the gradient of the loss function over parameter θ. The function expression of $J(\theta)$ is shown in *Equation (4)*.

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y_i \log(y_i) + (1-y_i)\log(1-y_i))] \quad \text{(Eq.4)}$$

In *Equation (4)*, m represents the number of samples; y_i represent the true label of the i-th sample; y_i represents the predicted probability of the i-th sample; θ represents model parameters. The formula for calculating the size of feature maps after convolution operation is shown in *Equation (5)*.

$$O = \frac{I + 2M - K}{S} + 1 \quad \text{(Eq.5)}$$

In *Equation (5)*, O represents the size of the output feature map; M indicates the fill size; S shows the step size. ResNet50 is suitable for remote sensing classification research with limited data, and can achieve good classification accuracy in situations with limited data. However, when the data is too complex and large, ResNet50 still has significant limitations. Therefore, in order to improve the shortcomings of merchants and further enhance the accuracy of remote sensing plant identification, the study adopts the introduction of EfficientNet algorithm to integrate it with ResNet50. When the data is small, lightweight ResNet50 is used for image recognition, and EfficientNet is used for recognition when the data is large. As shown in *Figure 2*, EfficientNet series networks have stronger classification capabilities, more reasonable internal structure design, and more efficient operation. EffiuientNet can comprehensively consider three factors: depth, width, and resolution, and is internally stacked with MBConv blocks.

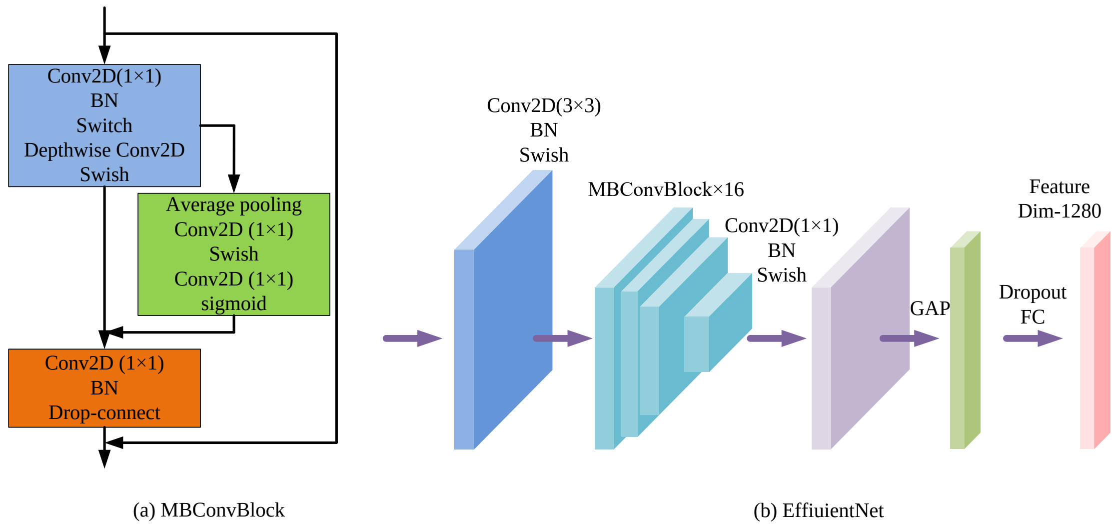

Figure 2. *EfficientNet network module and its structure*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

Among them, the calculation formula for MBConv block is shown in *Equation (6)*.

$$b = SE(DepthwiseConv(a, w_d)) \times a \tag{Eq.6}$$

In *Equation (6)*, b represents the output of the MBConv block; a represent the feature map of EfficientNet input; w_d represents the weight of deep convolution kernels. EfficientNet optimizes the network structure by uniformly extending depth, width, and resolution, as expressed in *Equation (7)*.

$$FLOP_s \propto D \times W^2 \times R^2 \tag{Eq.7}$$

In *Equation (7)*, D represents the depth of the network; W indicates network width; R represents the resolution of the input image. EfficientNet is extended by a composite scaling factor ϕ and fixed scaling parameters α, β, γ as shown in *Equation (8)*.

$$\begin{cases} D = \alpha^{\varnothing} \\ W = \beta^{\varnothing} \\ R = \gamma^{\varnothing} \end{cases} \tag{Eq.8}$$

In *Equation (8)*, α, β, γ represents the growth rate of control depth, width, and resolution, respectively, and $\alpha \times \beta^2 \times \gamma^2 \approx 2$. Compared to other network models, EffiUentNet series networks can maintain high classification accuracy with a small number of model parameters. However, EffiUentNet is prone to overfitting when dealing with small data, and ResNet50 can effectively avoid this drawback. The overall recognition model can be divided into four stages, namely preprocessing stage, feature extraction stage, model training stage, and recognition application stage. The preprocessing stage is mainly used for cleaning and formatting image data for subsequent processing. The feature extraction stage converts image data into feature vectors that can be processed by deep learning models (Bhandari et al., 2019; Abd-Elaziz et al., 2020). During the model training phase, the optimal model parameters are searched for based on the Lightweight ResNet50+EffiUentNet to achieve more efficient and accurate recognition of plant remote sensing images. The final recognition application stage applies the trained model to new image data to complete recognition.

Therefore, the model processing flow combining lightweight ResNet50 and EffiUentNet (Lightweight ResNet50+EffiUentNet) is shown in *Figure 3*. In the figure, starting with the lightweight design of ResNet50, the first residual block is adjusted to 64*64*256. Then, two 3*3 convolution kernels are used to replace the original 7*7 convolution kernel, and a 3*3 max pooling layer is introduced. Next, introduce EfficientNet to address big datasets.The data set used in the study, the PlanTCLEF 2019 Plant Species Identification Dataset, covers 10,000 remote sensing images from multiple geographic regions around the globe, containing 1,000 different plant types. The dataset contains a diverse range of plant species, including herbs, shrubs and trees, from a variety of ecological Settings, such as urban green Spaces, nature reserves and agricultural land. These images were acquired under different acquisition conditions and covered a variety of growth states and environmental factors, ensuring the diversity and representation of

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

the data. The universality and complexity of this dataset make the research model more applicable and universal in real world applications, and can effectively cope with plant identification and monitoring tasks under various environmental conditions. The combination of EfficientNet and ResNet50 provides superior performance and efficiency for processing large data sets. EfficientNet uses compound scaling to achieve higher accuracy and lower computing costs by simultaneously adjusting the depth, width, and resolution of the network. Compared to traditional network architectures, EfficientNet is optimized in terms of the number of parameters and computational complexity, making it extremely suitable for processing large-scale image data. Its lightweight design not only enhances the inference speed of the model, but also shows better performance in image classification and feature extraction, especially when processing complex plant remote sensing images. EfficientNet was selected as a supplement because of its ability to significantly reduce resource consumption while maintaining high accuracy, providing the ideal balance for processing large data sets. During the training phase, the cross entropy loss function is used for optimization to find the optimal model parameters. Finally, the trained model is applied to new image data to complete the recognition task.

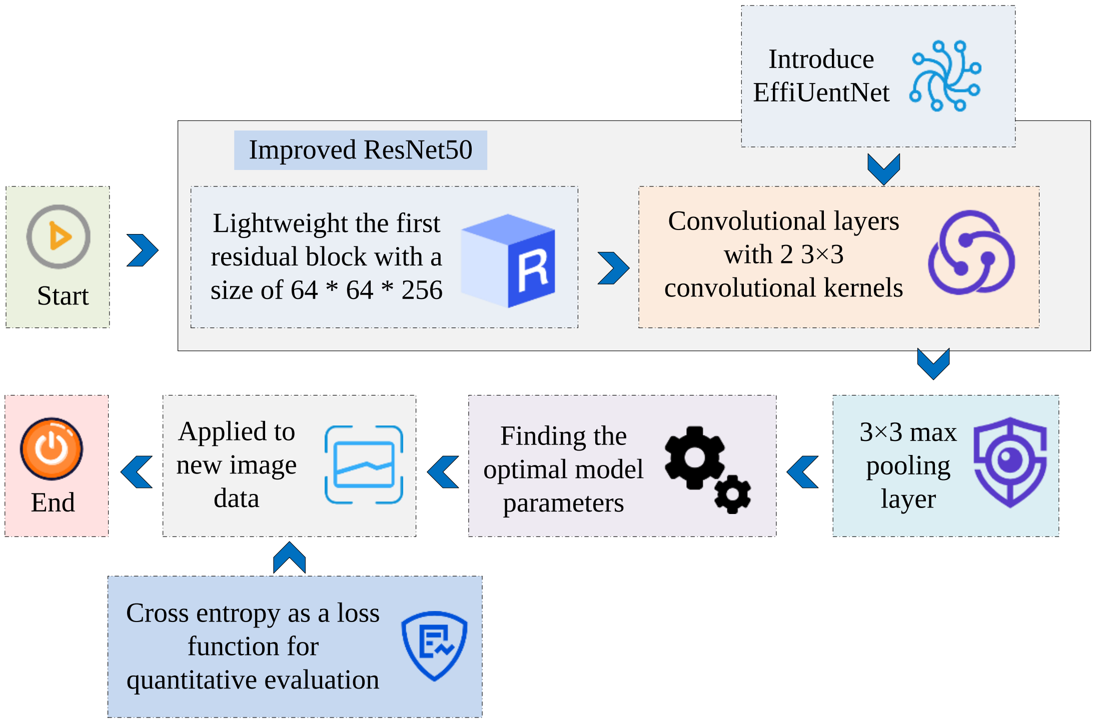

Figure 3. *Lightweight ResNet50+EffiUentNet model processing flow*

Remote sensing image processing and feature extraction method based on Lightweight ResNet50+EffiUentNet

In landscape design, accurate plant image recognition technology can provide key data support to help designers make scientific and reasonable decisions in the planning and maintenance process. Among them, image preprocessing and effective feature extraction of plant remote sensing images are the key to achieve good recognition performance of the model (Bhandari, 2020; Choudhuri et al., 2023). The training process of the whole model depends on a large number of plant remote sensing image data, and the feature

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

extraction and learning of the model are carried out, and the recognition results are finally output. *Figure 4* shows the training process of the overall model. In *Figure 4*, the whole model preprocesses the image data, inputs the processed data into the model, performs feature extraction and learning through the model, and finally outputs the recognition result. By analyzing the difference between the recognition results and the real label, the model parameters are updated by using backpropagation to realize the model optimization. In the actual model training process, to realize the model operability and visualization, a series of auxiliary tools are designed and implemented, such as model structure visualization, training process visualization, etc., to ensure the understanding and control of each step, and at the same time realize the monitoring and optimization of model performance. Data acquisition is the first step to realize plant RSI recognition data acquisition is divided into image acquisition and label collection, image acquisition is to obtain the plant RSI to be identified, and label acquisition is to obtain the real label of the corresponding image. Therefore, it is necessary to collect data from multiple aspects when realizing image recognition (Kong and Ge, 2021; Zuo et al., 2022; Cao et al., 2023; Wang and Rosen, 2023).

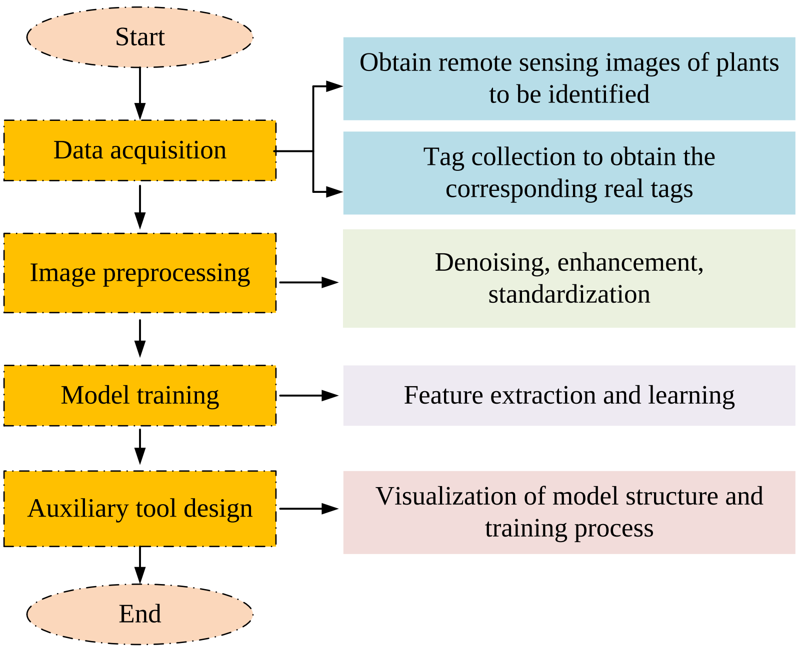

Figure 4. *Improving the ResNet50 model training process*

In this study, several key changes were made to the ResNet50 architecture to improve its performance in remote sensing plant image recognition, especially in terms of convolutional layers and pooling layers. First, the design of the convolutional layer was optimized, and smaller convolutional cores (such as 3×3) and shallower network layers were used in the study to reduce the computational complexity and preserve the local features of the image (Han et al., 2020; Li et al., 2021; Ebrahimi et al., 2022; Luo et al., 2023). This lightweight design helps to reduce model parameters and improve computational efficiency, while extracting key image information efficiently. In addition, the Pooling layer is changed to the combination of Max Pooling and Average Pooling, which makes the dimension reduction of the feature map more effective, while

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

maintaining the spatial structure of important features. Such a design aims to improve the reasoning speed and overall efficiency of the model in the case of limited resources by reducing redundant information, thus making the model more suitable for real-time applications. These changes not only optimize the performance of the model, but also enhance its adaptability in complex environments, showing good versatility and accuracy. Among them, image preprocessing includes image denoising, contrast adjustment and brightness adjustment. The function expression of image denoising is shown in *Equation (9)*.

$$I_{denoised}\left(x,y\right)=\sum\nolimits_{i=-k}^{k}\sum\nolimits_{j=-k}^{j}I\left(x+i,y+j\right)\times G(i,j) \quad \text{(Eq.9)}$$

In *Formula (9)*, $I_{denoised}$ represents the image matrix after denoising; $G(i,j)$ indicates the weight of the Gaussian filter. Contrast adjustment Improves image visibility by pulling up the pixel value range. Linear contrast stretching can be shown in *Equation (10)*.

$$I_{conteasted}=\frac{(I-I_{\min})\times(O_{\max}-O_{\min})}{I_{\max}-I_{\min}}+O_{\min} \quad \text{(Eq.10)}$$

In *Formula (10)*, $I_{conteasted}$ represents the image matrix after contrast adjustment; $I_{\min}, I_{\max}$ represent the minimum and maximum pixel values in the original image; $O_{\min}, O_{\max}$ represent the minimum and maximum pixel values of the expected output image, respectively. Brightness adjustment increases or decreases the brightness of the image by adding a constant value, as in *Equation (11)*.

$$I_{brightened}=I+\sigma \quad \text{(Eq.11)}$$

In *Formula (11)*, $I_{brightened}$ represents the image matrix after brightness adjustment; σ represents the brightness adjustment amount. Therefore, the image enhancement synthesis formula is shown in *Equation (12)*.

$$I_{enhanced}=\tau\times(I_{denoised}-I_{mean})+\sigma\times I_{brightened} \quad \text{(Eq.12)}$$

In *Formula (12)*, τ represents the adjustment factor of contrast; I_{mean} represents the average value of the image after de-noising (Mehrtash et al., 2020; Clough et al., 2020; Eelbode et al., 2020). The above steps can significantly improve image quality and create better conditions for feature extraction and classification of the Lightweight ResNet50+EffiUentNet. By adjusting the parameters in these processes, the effect of image preprocessing can be optimized according to specific problems. Next, the fully connected layer outputs the recognition results and updates the model parameters through the backpropagation algorithm to achieve optimization (Houssein et al., 2021; Jawad et al., 2021; Gao et al., 2022). Through continuous training and analysis, the model can obtain the state and change trend of plant images, predict and judge, and provide important data support for landscape design. Through feedback mechanism and adaptive technology, the Lightweight ResNet50+EffiUentNet continuously optimizes the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

recognition strategy, improves the accuracy and real-time recognition, and thus improves the efficiency of landscape design and the quality of user experience.

Demand analysis is the key to program development, and user needs analysis is crucial for aquatic plant image recognition systems. The system can efficiently identify images of aquatic plants, help environmental protection personnel monitor, identify, and protect aquatic plants, and also provide an identification platform for interested users (Syriopoulos et al., 2021; Karaman et al., 2023). The main functions include user image uploading, image recognition, and recognition result display. The user uploads the image through the We Chat Mini Program, uses a neural network model to identify it in the background, and finally displays the results in the Mini Program. The system design includes the system architecture, workflow, and functional modules (Ghazal et al., 2022). The system hardware supports AMD Phenomenon, the development languages include PHP, WXML, WXSS, Javascript and Python, the operating system is Win7, and the server is Apache Ubuntu 18.04. The system architecture includes a view layer, a business logic layer, and a technical service layer (Soltani Firouz and Sardari, 2022). The workflow of the Aquatic Plant Identification System is shown in *Figure 5*.

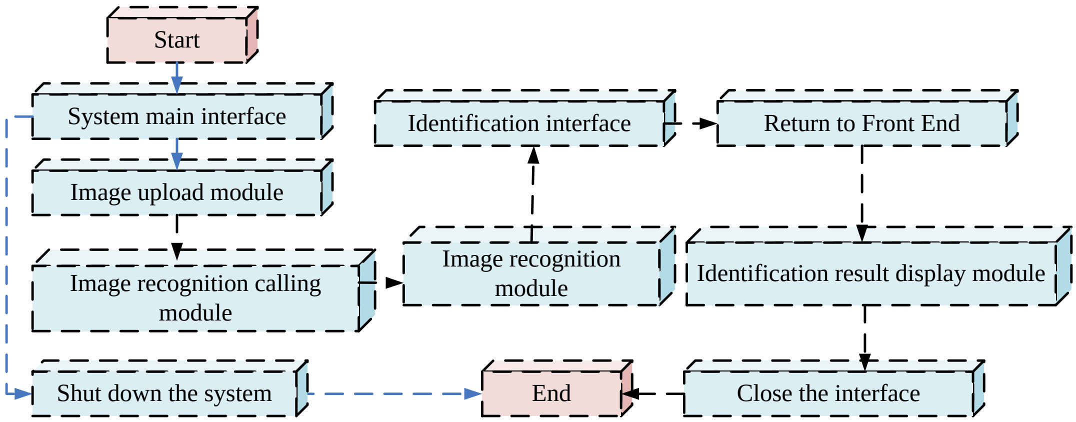

***Figure 5.** Workflow of aquatic plant identification system*

In *Figure 5*, when the user takes a picture that needs to be recognized, log in to the operation page of the WeChat Mini Program, upload the image to the specified path inside the server, and then call the Python file with the saved model file, and the model starts to be recognized. Finally, the recognition result is sent back to the front-end page in JSON format, and the end user gets the identification information (Pei et al., 2021). The remote sensing image processing and feature extraction method based on Lightweight ResNet50+EffiUentNet model is shown in *Figure 6*.

In *Figure 6*, the RSI of the plant to be identified is first obtained, and then preprocessed, including denoising and enhancement, to improve the image quality. The preprocessed images will be fed into the Lightweight ResNet50+EffiUentNet for feature extraction and then into the classification process. In the classification process, the model will learn the relationship between image features and plant categories and make recognition decisions. To improve the recognition accuracy and real-time performance of the model, the model will be trained and optimized by backpropagation and gradient descent. The optimized model can not only optimize its identification strategy and decision-making process, but also provide landscape designers with a large amount of

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

real-time data to help them understand the specific conditions of the current environment, such as plant species, growth status, etc., which can help designers make more realistic design decisions.

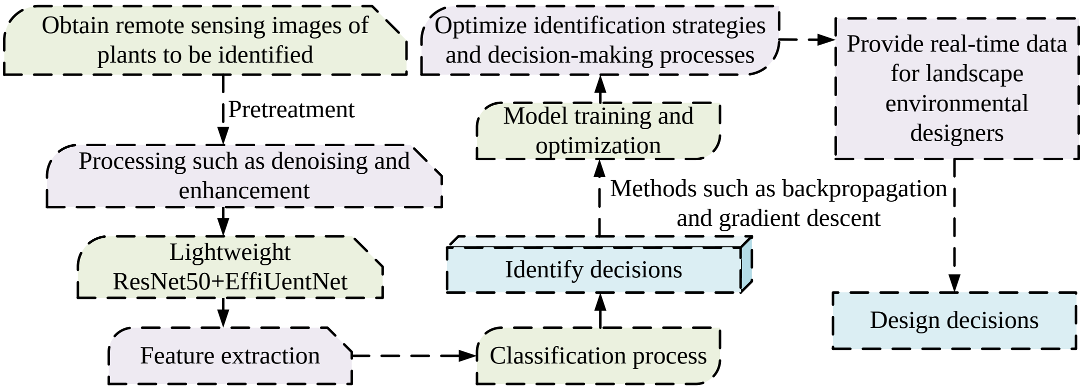

Figure 6. *Flowchart of plant RSI recognition based on Lightweight ResNet50+EffiUentNet*

Simulation experiment setting and result analysis

The parameters of the Lightweight ResNet50+EffiUentNet were set and optimized, which was to make the model better adapt to the task of plant RSI recognition. Then, the optimized model is used to carry out recognition experiments on the actual RSIs, and the experimental results are analyzed in depth. The analysis will be presented in the form of charts to help you understand the performance of the model and the specific effect of the optimization strategy.

Lightweight ResNet50+EffiUentNet parameter setting and optimization

Indeep learning, ResNet50 is a commonly used network structure, and its powerful feature extraction ability makes it excellent in various tasks. However, in order to adapt to the particularity of plant RSIs, the optimization and parameter setting of ResNet50 are particularly important. Firstly, with RSIs, the convolution kernel size, step size and other parameters of the network were adjusted to improve the network's ability to recognize small targets and details; secondly, the complexity of the network was controlled by introducing regularization terms to prevent the occurrence of over fitting; finally, the most suitable model configuration for RSI processing was selected by comparing different activation functions and Adam. The research experimental environment includes Intel ® Core? I9-10900K CPU, NVIDIA GeForce RTX 3090 GPU, 64GB DDR4 RAM, Ubuntu 20.04.1 LTS operating system, and Python 3.8.5 programming language. *Table 1* lists the parameter settings of the model.

The PlanTCLEF 2019 Plant species Identification dataset contains 10,000 images covering 1,000 plant species, which is obtained by visiting the official PlanTCLEF website. Designed specifically for plant species recognition research, the dataset covers 1,000 different plant species, each of which provides multiple image samples to help improve the model's recognition ability when processing a wide variety of plant images. The study selects 10 plant types from the dataset and enhances each image to a total of 300 images for model training. The allocation of the dataset is as follows: 70% (2100 sheets) for training, 15% (450 sheets) for validation, and 15% (450 sheets) for testing.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

This allocation strategy ensures that the model is fully learned in the training process, and the number of validation and test samples is sufficient to ensure the accuracy of model performance evaluation. The main metrics used in the study to evaluate model performance include accuracy, accuracy, recall, and F1 values. Accuracy measures the proportion of samples correctly classified by the model, accuracy reflects the proportion of samples correctly predicted as positive samples in all predicted positive samples, recall rate represents the proportion of samples correctly predicted as positive samples in all actual positive samples, and F1 value is the harmonic average of accuracy and recall rate, providing a comprehensive evaluation of model performance. The evaluation of these indicators on different data sets helps to understand the robustness and generalization ability of the model and ensure its applicability in remote sensing images of diverse plants. In addition, the study also considers computational efficiency, including training time and prediction time. Through comparative analysis, it shows that the improved model can ensure high accuracy while reducing computational resource time, thus supporting the claim of improving efficiency. The performance analysis of model structure tuning is shown in *Figure 7*.

Table 1. *System parameter*

Item	Description	Item	Description
CPU	Intel® Core™ i9-10900K CPU @ 3.70GHz	Learning Rate	0.001
GPU	NVIDIA GeForce RTX 3090	Batch Size	32
RAM	64GB DDR4	Training Epochs	100
Operating System	Ubuntu 20.04.1 LTS	Dataset	PlantCLEF2019 Plant Species Recognition dataset
Programming Language	Python 3.8.5	Dataset Size	10,000 images
Deep Learning Library	PyTorch 1.7.0	Dataset Split	Training: 70%, Validation: 15%, Test: 15%
ResNet50 Model	torchvision.models.resnet50 (pretrained=True)	Adam	Adam

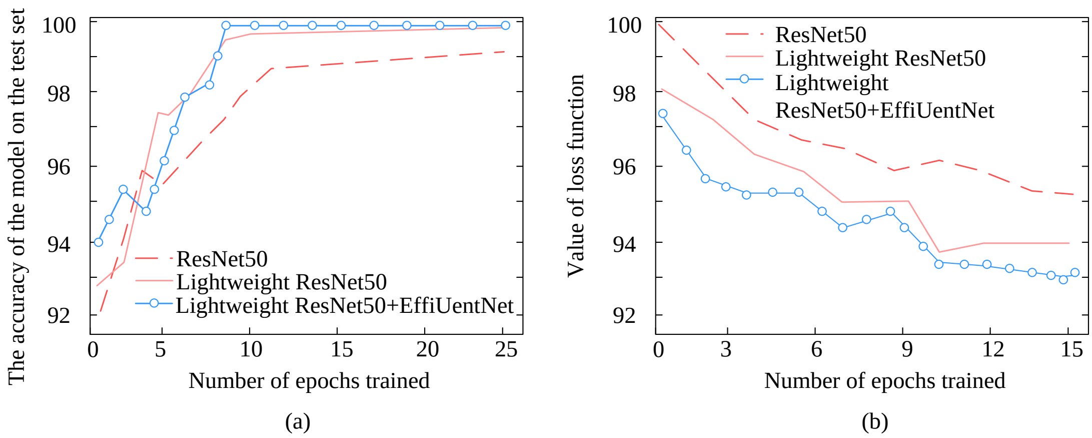

Figure 7. *Performance analysis of model structure adjustment for improved ResNet50. (a) The accuracy of the model on the test set; (b) The loss value function of the model on the test set*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

In *Figure 7*, in order to verify the relevant performance of Lightweight ResNet50+EffiUentNet, the research selected to compare and verify it with the original ResNet50 model and Lightweight ResNet50 model. *Figure 7* shows the results of three of the 25 independent runs and the optimal performance change curve within the first set. In *Figure 7*, the Lightweight ResNet50+EffiUentNet learns rapidly in the early stage and decreases in the later learning, and finally obtains the best accuracy of 99.78% around the 10th epoch. In *Figure 7(b)*, although the model has achieved good performance around the 10th epoch, it has not yet fully converged within the group, and with the continuous training, the performance of each group finally reached the global optimal and converged around the 15th epoch. Based on the performance of the optimized model, the study can analyze the impact of model parameter settings, as shown in *Figure 8*.

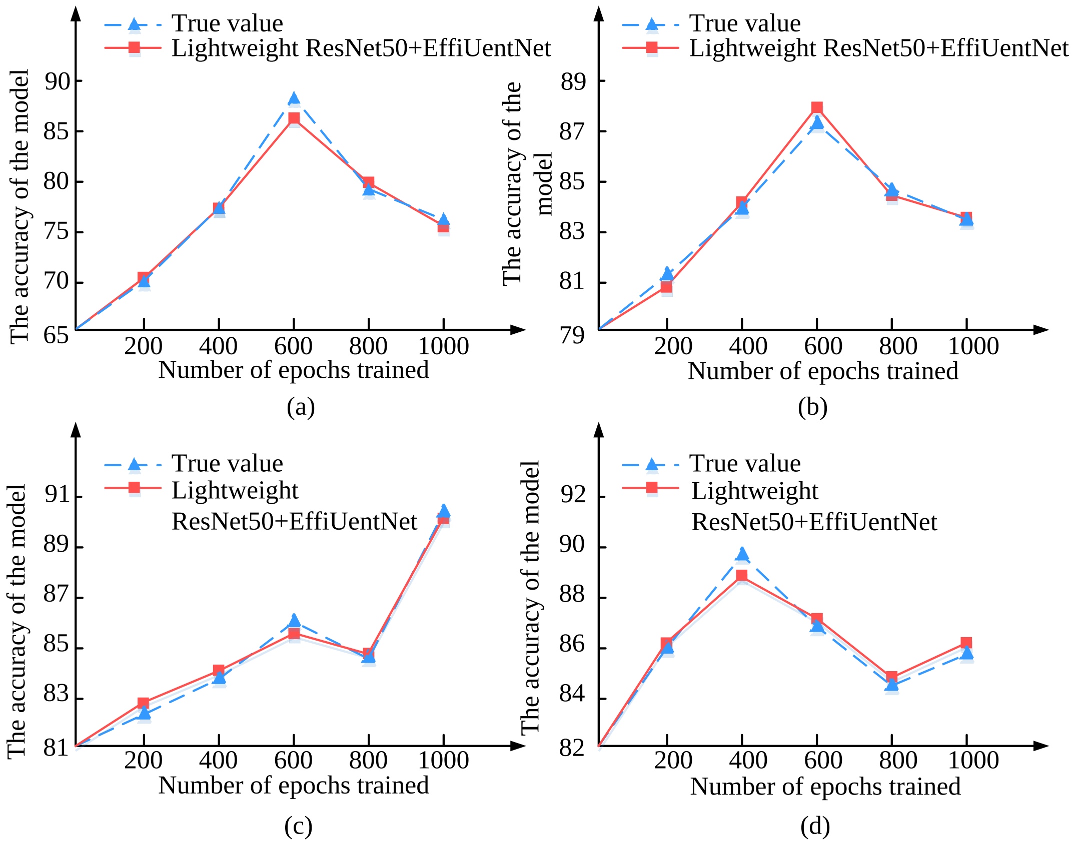

***Figure 8.** Influence of parameter settings on model performance. (a) Model accuracy with learning rate of 0.001 over epochs; (b) Model Accuracy with adam optimizer over epochs; (c) Model accuracy with batch size of 32 over EpochConvergence curve of NSGA-II throughput; (d) Model accuracy with regularization weight of 0.01 over epochs*

Figure 8 shows that when the learning rate is set to 0.001, the accuracy of the model gradually improves to a maximum of 87% after 600 epochs, and then remains stable. In *Figure 8(b)*, the model achieves an accuracy of 88.5% after 600 epochs, showing better performance. *Figure 8(c)* shows the maximum accuracy after 1000 epochs, i.e., 90.2%, when the batch size is set to 32. In *Figure 8(d)*, when the weight of the regularization term is set to 0.01, the model achieves a maximum accuracy of 89.1% after 400 epochs. Compared with other parameter settings, this setting improved the accuracy on the test

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

set by 9.2%, effectively improving the model performance. According to the change of accuracy during model training, the learning curve of the model was plotted, as shown in *Figure 9*.

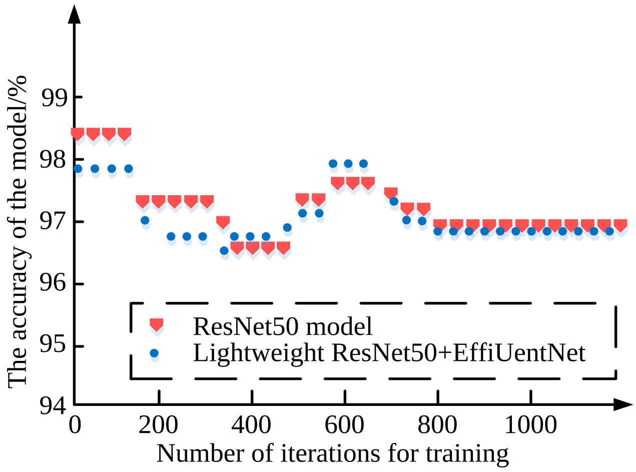

Figure 9. *Learning curve of the lightweight ResNet50+EffiUentNet*

In *Figure 9*, the Lightweight ResNet50+EffiUentNet was used and iteratively trained. As iterations increased, model's accuracy gradually improved and tends to be stable, which indicated that the model converged and found an optimal solution, thereby reducing the error on the validation set. At the same time, the performance remained stable during the iterative process, which further proved the effectiveness of the model and parameter optimization strategy and improved the overall performance of the model.

Plant RSI recognition experiment and result analysis based on improved ResNet50

These parameter optimization strategies are important in the performance and accuracy of the model, and then based on the optimized model, the actual plant RSI recognition experiment was carried out, and the results were analyzed in depth to verify the practical application effect and performance of the model. To measure the performance of the improved ResNet50 model, Lightweight ResNet50+EffiUentNet was compared with the original ResNet50 model, VGG16 model and InceptionV3 model, and experimental results of remote sensing plant image recognition were compared with other methods. As shown in *Figure 10*.

As shown in *Figure 10*, the best recognition results are obtained after iterative training of the Lightweight ResNet50+EffiUentNet. It had an average accuracy of 91.6% and an F1 value of 0.92 on the test set. *Figure 10(b)* shows the recognition results of other common models (such as the original ResNet50, or other deep learning models) on the same dataset, with an average accuracy of 81.2% and an F1 value of 0.82. Compared with other methods, the average accuracy of the Lightweight ResNet50+EffiUentNet was increased by 10.4%, and the F1 value was increased by 12.2%, which was significantly better than other commonly used models. To measure the performance of improved ResNet50, the study compared it to the original ResNet50 model, VGG16 model, and InceptionV3 model, and the results are shown in *Figure 11*.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

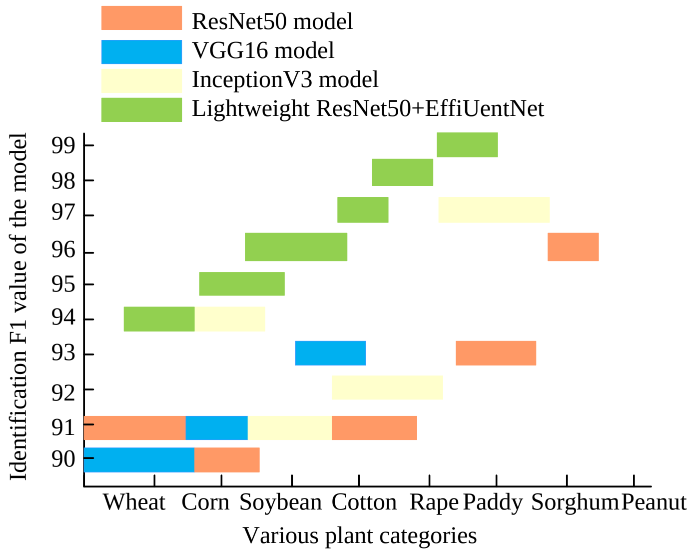

***Figure 10.** Comparison between Lightweight ResNet50+EffiUentNet and other methods*

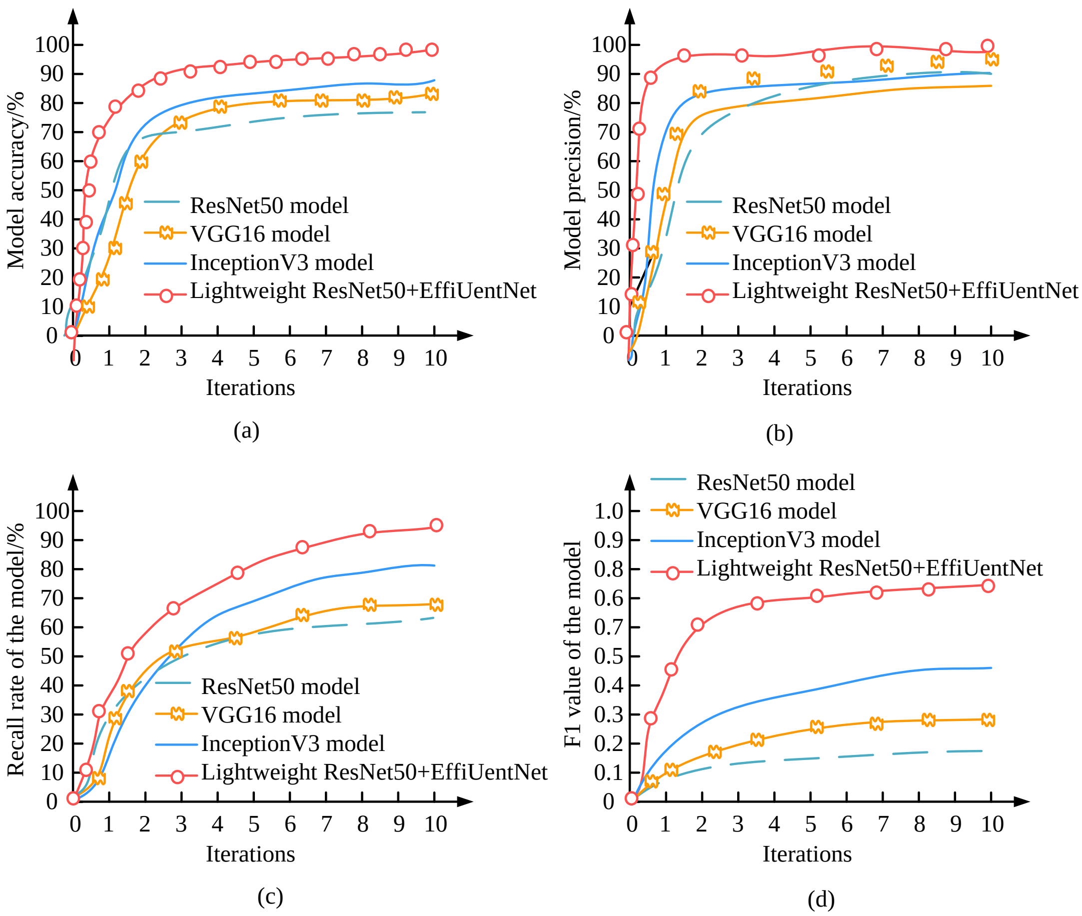

***Figure 11.** Comparison of plant RSI recognition performance based on lightweight ResNet50+EffiUentNet. (a) Comparison of accuracy for different models over iterations; (b) Comparison of precision for different models over iterations; (c) Comparison of recall for different models over iterations; (d) Comparison of F1 score for different models over iterations*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

Figures 11, 11(b), 11(c), and 11(d) represent the accuracy, precision, recall, and F1 values of the four models respectively. In *Figure 11*, the accuracy, precision, recall, and F1 values all increased as iterations increased. It is evident that the Lightweight ResNet50+EffiUentNet performed the best at the same number of iterations. The original ResNet50 model, VGG16 model, InceptionV3 model and Lightweight ResNet50+EffiUentNet had the highest accuracy of 85.59%, 88.21%, 90.63% and 96.82%, the highest accuracy of 86.28%, 89.66%, 91.23% and 97%, the highest recall rates of 84.76%, 87.47%, 90.27% and 96.25%, respectively, and the highest F1 values of 85.38%, 88.06%, 90.81% and 96.62%, respectively. The interpretability analysis results of the Lightweight ResNet50+EffiUentNet in plant RSI recognition are shown in *Figure 12*.

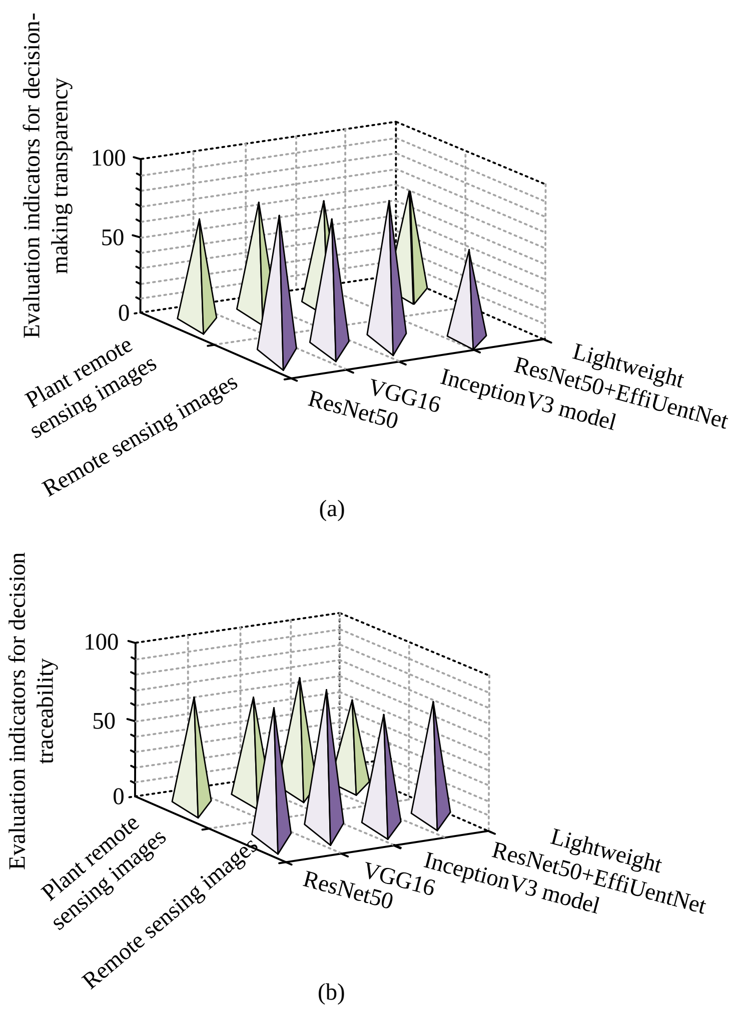

Figure 12. *Interpretability analysis of lightweight ResNet50+EffiUentNet in RSI recognition. (a) Comparison of decision transparency for different ModelsClear game rules; (b) Comparison of decision traceability for different models*

In model evaluation, interpretability and traceability are important indicators for measuring the transparency of model decision-making. Interpretability refers to the clarity of the model's decision-making process, enabling users to understand how the model generates predictive results. Traceability refers to the traceability and validation of

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

every step in the decision-making process. In *Figure 12*, the Lightweight ResNet50+EffiUentNet demonstrates good interpretability. In the traditional ResNet50, VGG16 and InceptionV3 models, due to the complexity and black box of the model's decision-making process, the interpretability of the decision-making process is relatively weak, resulting in a low understanding and trust of the model's decision-making process. Lightweight ResNet50+EffiUentNet introduces visualization technology to achieve clear display of feature extraction and decision-making processes, making the decision-making process of the model not only transparent but also verifiable. These technologies present complex internal mechanisms of models in an intuitive way, thereby enhancing understanding and trust in model behavior, resulting in higher scores in interpretability. In terms of specific evaluation indicators, the evaluation indexes of the traditional ResNet50 model, VGG16 model, InceptionV3 model and the Lightweight ResNet50+EffiUentNet were 82%, 86%, 88% and 96% in decision transparency, 80%, 84%, 88% and 94% in decision traceability, and 81%, 85%, 87% and 95% in model comprehension, respectively. It can be seen that the interpretability of improved ResNet50 in the plant RSI recognition task is the best. The overfitting and underfitting analysis of the Lightweight ResNet50+EffiUentNet on the plant RSI recognition task, as well as the results of the computational efficiency analysis, are shown in *Figure 13*.

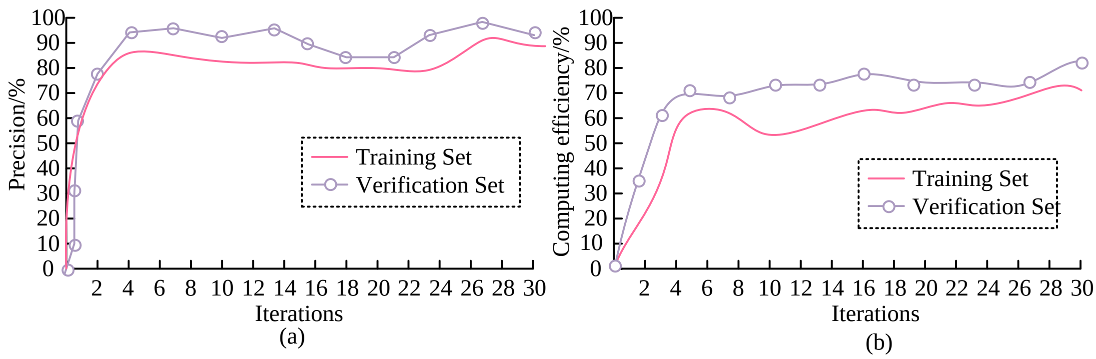

Figure 13. *Performance of the lightweight ResNet50+EffiUentNet on the training and validation sets. (a) Accuracy of lightweight ResNet50+EffiUentNet model; (b) Lightweight ResNet50+EffiUentNet model computational efficiency*

In *Figure 13*, the performance of Lightweight ResNet50+EffiUentNet on both the training set and the validation set was relatively stable, and the model did not show overfitting or underfitting. Among them, the average accuracy on the training set reached 98%, and the average accuracy on the validation set also reached 96%, showing good generalization ability. *Figure 14* illustrates the computational efficiency of the model, including training time and prediction time.

In *Figure 14*, the Lightweight ResNet50+EffiUentNet has high computational efficiency while maintaining performance. The average training time of the model was 94.28 seconds, and the average prediction time was 95.16 seconds. This showed that the Lightweight ResNet50+EffiUentNet not only performed well in plant RSI recognition tasks, but also had efficient computational performance.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

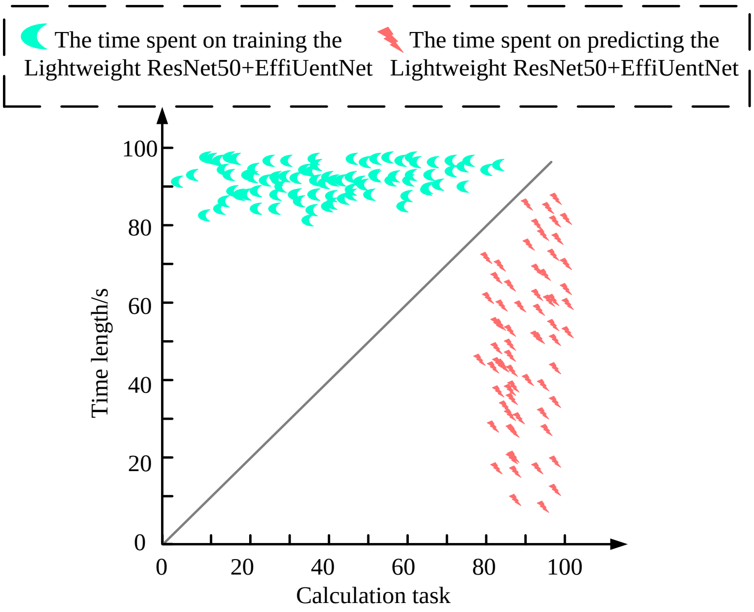

Figure 14. *Computational efficiency of the Lightweight ResNet50+EffiUentNet*

Figure 15 shows the results of the Lightweight ResNet50+EffiUentNet model in plant recognition tasks. Through the recognition results of this model, it can be seen that it can accurately recognize the categories of various plants, verifying its effectiveness in processing plant image classification tasks. Lightweight ResNet50+EffiUentNet combines lightweight architecture and efficient feature extraction methods, enabling it to maintain high performance and accuracy in complex environments. Therefore, this model can be used to process diverse and complex plant image data. In order to analyze the effect of the proposed model in practical application, the research was carried out through the actual urban green space planning and ecological detection, and the verification effect was shown in *Table 2*.

(a) (b)

Figure 15. *Plant recognition results. (a) Emergent plant image; (b) Submerged plant image*

In the results of *Table 2*, the accuracy of the improved ResNet50 in urban green space planning reached 96.82%, F1 value was 0.96, accuracy was 97.00%, and recall rate was 96.25%. This high performance indicates that the model has a strong ability to identify plant species, and can provide detailed and reliable basic data for the optimal layout of urban green space. The accuracy of the improved ResNet50 in ecological monitoring

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

reached 94.76%, and the F1 value was 0.95, which showed the strong ability of the model in real-time monitoring of plant health status. The results show that the proposed method improves the efficiency of feature extraction and classification, making the model not only significantly superior to the traditional model in accuracy, but also better robust in processing complex and high-dimensional images.

Table 2. *The actual verification results of different models*

Case	Method	Precision (%)	F1 value	Accuracy (%)	Recall (%)	Time (s)
Urban green space planning	Improved ResNet50	96.82	0.96	97.00	96.25	3.2
	Original ResNet50	85.59	0.85	86.28	84.76	3.1
	VGG16	88.21	0.88	89.66	87.47	3.5
	InceptionV3	90.63	0.91	91.23	90.27	3.3
Ecological monitoring	Improved ResNet50	94.76	0.95	95.3	94.20	2.8
	Original ResNet50	82.10	0.81	83.00	81.00	2.9
	VGG16	86.80	0.87	87.5	86.50	3.0
	InceptionV3	89.77	0.90	90.1	88.80	3.2

Discussion

The improved ResNet50 and EfficientNet models were used to achieve remarkable results in the field of remote sensing plant image recognition. The results show that the average accuracy of the improved model on the test set is 91.6%, and the F1 value is 0.92, which is significantly better than the results of traditional methods and previous studies. This shows that the introduction of deep learning technology can effectively improve the accuracy of plant identification, especially in complex natural environments, and such methods show strong robustness. Compared with previous studies, Soltani Firouz and Sardari (2022) proposed a method combining machine vision (MV) and image processing (IP) to detect defective areas of products, aiming at the problem that agricultural production efficiency is affected by multiple defects. The harvested produce is photographed by a specific camera under appropriate lighting conditions and evaluated using image processing technology, which ultimately allows the product to be classified based on the detected defects. A variety of classification algorithms can be used to efficiently classify products according to quality and defect types, thereby improving the defect detection efficiency of harvested products (Soltani Firouz and Sardari, 2022). Pei et al. (2021) proposed the importance of geographic information science (GIScience) and remote sensing and their applications in the research, aiming at the dual challenges of data and computing intensity in the research of natural resources and environment science, so as to obtain the prediction of future development direction. Research the definition and framework of clarifies two disciplines. GIScience focuses on the abstract expression of basic concepts and laws of geography, and takes ecological modeling, geographical analysis and geographical calculation as the main research framework. Remote sensing technology, on the other hand, is a mechanism to comprehensively cope with human's impact on the natural ecological environment. It obtains data by observing the Earth surface system, and its main fields include sensors and platforms, information processing and interpretation, and the application of natural resources and environment (Pei et al., 2021). Compared with the methods proposed in references Soltani Firouz and

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

Sardari (2022) and Pei et al. (2021), the improved ResNet50 method has significant advantages in remote sensing plant image recognition. First of all, the deep learning model has a higher accuracy of 91.6% in complex natural environments, while the machine vision and image processing methods in literature (Soltani Firouz and Sardari, 2022) are greatly affected by environmental conditions and rely on manual setting and multiple optimization. Secondly, the ResNet50 method has a high degree of automation, which can efficiently process a large amount of image data and reduce manual intervention, while the traditional method requires more manual operation and adjustment during processing. Finally, the improved ResNet50 model is optimized for remote sensing image recognition tasks and has strong adaptability, which can handle larger scale and more complex image data, showing stronger practicability and processing ability than the traditional method.

The study emphasizes the importance of architecture optimization and data enhancement in the model training process, which not only improves the recognition ability of the model under various plant species, but also reduces the consumption of computing resources. In addition, the computational efficiency of the studied model is improved during the training process, the average training time is 94.28 minutes, and the prediction time is 95.16s, which makes it more suitable for practical application scenarios.

The application of ResNet50 model in remote sensing plant image recognition will provide strong support for landscape architects, urban planners and environmental scientists. First of all, landscape designers can use the model to conduct detailed plant species and growth state analysis, optimize green space layout, and improve the aesthetics and ecological functions of the design. Secondly, urban planners can scientifically plan urban Spaces and enhance the sustainability of ecosystems by monitoring the health status and biodiversity of urban green Spaces in real time. In addition, environmental scientists can use the model to study ecological changes in depth, assess the impact of human activities on the natural environment, and develop appropriate conservation measures.

In the context of artificial intelligence, research utilizing improved deep learning models, such as ResNet50 and EfficientNet, exemplifies the power of AI in processing large data sets. These models automatically recognize and learn patterns from complex data through multi-layer neural networks, far exceeding the limitations of traditional methods that rely on manual feature design and selection. In environmental design applications, artificial intelligence, with its efficient learning mechanism, can analyze and interpret remote sensing images of plants in real time, significantly improving recognition accuracy and decision-making efficiency. This advantage enables environmental designers and urban planners to develop scientific planning solutions based on real-time, accurate data to effectively address ecological challenges and achieve sustainable development. Therefore, the application of artificial intelligence not only optimizes the environmental design process, but also promotes the intelligent transformation of ecological management.

Conclusion

The research successfully demonstrated the effective application of the improved ResNet50 and EfficientNet models in remote sensing plant image recognition, and the specific results showed that the models achieved high performance indexes such as accuracy and F1 value. Key findings show that deep learning technology can not only improve the accuracy of plant species identification, but also optimize resource

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

utilization, thus providing reliable data support for landscape environmental design and ecological monitoring tasks. These findings have important practical applications and can provide actionable tools for landscape architects, urban planners and environmental scientists to help achieve the Sustainable Development Goals. Although the improved ResNet50 and EfficientNet models in this study achieved significant results in remote sensing plant image recognition, they still face some challenges when applied to large-scale data sets or diverse environmental conditions, such as the training time and computational resource requirements of the models can increase significantly, especially when dealing with complex natural scenes. In addition, there may be security and privacy issues in practical applications, such as the collection and processing of sensitive ecological data, which may have an impact on the local ecological environment or relevant stakeholders. Therefore, future research directions can focus on further optimizing the computational efficiency and accuracy of the model, exploring compression techniques and adaptive algorithms to reduce the volume and resource requirements of the model. At the same time, research should focus on the interpretability and transparency of models to enhance trust in the decision-making process, and develop appropriate security protocols to ensure legality and ecological safety in the collection and use of data, thereby promoting sustainable development in the field of ecological research and urban planning.

Fundings. The research is supported by: This paper is a key sub-subject of the "Fourteenth Five-year Plan" of the Ministry of Education, Research on the Structure and Cultivation of College Teachers' Teaching Development Ability (No. JKY19020); Municipal level scientific research projects, Development and Application of Walls and Accessories in Guangxi's Distinctive Architecture (No. LD12005G).

REFERENCES

[1] Abd-Elaziz, M., Ewees, A. A., Yousri, D., Alwerfali, H., Awad, Q. A., Lu, S., Al-Qaness, M. (2020): An improved marine predators algorithm with fuzzy entropy for multi-level thresholding: Real world example of COVID-19 CT image segmentation. – IEEE Access 8: 125306-125330.

[2] Abdel-Basset, M., Chang, V., Mohamed, R. (2020): A novel equilibrium optimization algorithm for multi-thresholding image segmentation problems. – Neural Computing and Applications 33: 10685-10718.

[3] Bhandari, A. K., Ghosh, A., Kumar, I. V. (2019): A local contrast fusion based 3D Otsu algorithm for multilevel image segmentation. – IEEE/CAA Journal of Automatica Sinica 7(1): 200-213.

[4] Bhandari, A. K. (2020): A novel beta differential evolution algorithm-based fast multilevel thresholding for color image segmentation. – Neural Computing and Applications 32(9): 4583-4613.

[5] Cao, H., Wu, Y., Bao, Y., Feng, X., Wan, S., Qian, C. (2023): UTrans-Net: A model for short-term precipitation prediction. – Artificial Intelligence and Applications 1(2): 106-113.

[6] Choudhuri, S., Adeniye, S., Sen, A. (2023): Distribution alignment using complement entropy objective and adaptive consensus-based label refinement for partial domain adaptation. – Artificial Intelligence and Applications 1(1): 43-51.

[7] Clough, J. R., Byrne, N., Oksuz, I., Zimmer, V. A., Schnabel, J. A., King, A. P. (2020): A topological loss function for deep-learning based image segmentation using persistent homology. – IEEE Transactions on Pattern Analysis and Machine Intelligence 44(12): 8766-8778.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

[8] Dhanachandra, N., Chanu, Y. J. (2020): An image segmentation approach based on fuzzy c-means and dynamic particle swarm optimization algorithm. – Multimedia Tools and Applications 79(25-26): 18839-18858.
[9] Du, J., Lu, H., Hu, M., Zhang, L., Shen, X. (2021): CNN-based infrared dim small target detection algorithm using target-oriented shallow-deep features and effective small anchor. – IET Image Processing 15(1): 1-15.
[10] Ebrahimi, H., Rezaeian-Marjani, S., Galvani, S., Vahid, T. (2022): Probabilistic optimal planning in active distribution networks considering non-linear loads based on data clustering method. – IET Generation, Transmission & Distribution 16(4): 686-702.
[11] Eelbode, T., Bertels, J., Berman, M., Vandermeulen, D., Maes, F., Bisschops, R., Blaschko, M. B. (2020): Optimization for medical image segmentation: Theory and practice when evaluating with dice score or jaccard index. – IEEE Transactions on Medical Imaging 39(11): 3679-3690.
[12] El-Ghany, N., El-Aziz, S., Marei, S. (2020): A review: Application of remote sensing as a promising strategy for insect pests and diseases management. – Environmental Science and Pollution Research 27(27): 33503-33515.
[13] Fu, Z., Zheng, L., Li, J., Chen, G., Yu, T., Deng, T., Ynag, W. (2022): DMvLNet: Deep multiview learning network for blindly accessing image quality. – Journal of Electronic Imaging 31(5): 1-13.
[14] Gao, H., Fu, Z., Pun, C. M., Zhang, J., Kwong, S. (2022): An efficient artificial bee colony algorithm with an improved linkage identification method. – IEEE Transactions on Cybernetics 52(6): 4400-4414.
[15] Ghazal, T., Noreen, S., Said, R., Khan, M. (2022): Energy demand forecasting using fused machine learning approaches. – Intelligent Automation & Soft Computing 31(1): 539-553.
[16] Han, J., Moradi, S., Faramarzi, I., Zhang, H., Li, N. (2020): Infrared small target detection based on the weighted strengthened local contrast measure. – IEEE Geoscience and Remote Sensing Letters 18(9): 1670-1674.
[17] Houssein, E. H., Helmy, B. E. D., Elngar, A. A., Abdelminaam, D. S., Shaban, H. (2021): An improved tunicate swarm algorithm for global optimization and image segmentation. – IEEE Access 9: 56066-56092.
[18] Hu, T., Gong, W. (2021): Urban landscape information atlas and model system based on remote sensing images. – Mobile Information Systems 2021(4): 1-7.
[19] Hu, W. J., Xie, T. Y., Li, B. S., Du, Y. X., Xiong, N. N. (2021): An edge intelligence-based generative data augmentation system for IoT image recognition tasks. – Journal of Internet Technology 22(4): 765-778.
[20] Jawad, M., Dujaili, A., Ebrahimi, A., Fatlawi, A. (2021): Speech emotion recognition based on SVM and KNN classifications fusion. – International Journal of Electrical and Computer Engineering (IJECE) 11(2): 1259-1264.
[21] Karaman, A., Karaboga, D., Pacal, I., Akay, B., Basturk, A., Nalbantoglu, U., Coskun, S., Sahin, O. (2023): Hyper-parameter optimization of deep learning architectures using artificial bee colony (ABC) algorithm for high performance real-time automatic colorectal cancer (CRC) polyp detection. – Applied Intelligence 53(12): 15603-15620.
[22] Kattenborn, T., Eichel, J., Wiser, S., Burrows, L. (2020): Convolutional neural networks accurately predict cover fractions of plant species and communities in unmanned aerial vehicle imagery. – Remote Sensingin Ecology Conservation 6(4): 472-486.
[23] Kattenborn, T., Leitloff, J., Schiefer, F., Hinz, S. (2021): Review on Convolutional Neural Networks (CNN) in vegetation remote sensing. – ISPRS Journal of Photogrammetry and Remote Sensing 173(1): 24-49.
[24] Kong, X., Ge, Z. (2021): Deep learning of latent variable models for industrial process monitoring. – IEEE Transactions on Industrial Informatics 18(10): 6778-6788.
[25] Lauguico, S. C., Concepcion, R. S., Alejandrino, J. D., Tobias, R., Macasaet, D., Dadios, E. (2020): A comparative analysis of machine learning algorithms modeled from machine

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

vision-based lettuce growth stage classification in smart aquaponics. – International Journal of Environmental Science and Development 11(9): 442-449.
[26] Li, S., Wang, X., Yang, X., Zhang, K., Niu, S. (2021): Investigation of infrared dim and small target detection algorithm based on the visual saliency feature. – Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering 235(12): 1630-1647.
[27] Liao, Y., Ragai, I., Huang, Z., Kerner, S. (2021): Manufacturing process monitoring using time-frequency representation and transfer learning of deep neural networks. – Journal of Manufacturing Processes 68(8): 231-248.
[28] Liu, C., Lin, M., Rauf, H. L., Shareef, S. (2021): Parameter simulation of multidimensional urban landscape design based on nonlinear theory. – Nonlinear Engineering 10(1): 583-591.
[29] Luo, N., Yu, H., You, Z., Li, Y., Zhou, T., Han, N. (2023): Fuzzy logic and neural network-based risk assessment model for import and export enterprises: A review. – Journal of Data Science Intelligent Systems 1(1): 2-11.
[30] Lyu, P., He, L., He, Z., Liu, Y., Wei, Y. (2021): Research on remote sensing prospecting technology based on multi-source data fusion in deep-cutting areas. – Ore Geology Reviews 138(11): 104359-104375.
[31] Mehrtash, A., Wells, W. M., Tempany, C. M., Abolmaesumi, P., Kapur, T. (2020): Confidence calibration and predictive uncertainty estimation for deep medical image segmentation. – IEEE Transactions on Medical Imaging 39(12): 3868-3878.
[32] Morad, S. D., Mecca, R., Poudel, R. P. K., Liwicki, S., Cipolla, R. (2021): Embodied visual navigation with automatic curriculum learning in real environments. – IEEE Robotics and Automation Letters 6(2): 683-690.
[33] Pan, Y., Molin, Q., Guo, T., Zhang, L., Xue, X. (2021): Wireless passive surface acoustic wave (SAW) technology in gas sensing. – Sensor Review 41(2): 135-143.
[34] Pei, T., Xu, J., Liu, Y., Huang, X., Zhang, L., Dong, W., Qin, C., Song, J., Gong, J., Zhou, C. (2021): GIScience and remote sensing in natural resource and environmental research: Status quo and future perspectives. – Geography and Sustainability 2(3): 207-215.
[35] Reddy, C. S. (2021): Remote sensing of biodiversity: What to measure and monitor from space to species? – Biodiversity and Conservation 30(10): 2617-2631.
[36] Shan, P., Sun, W. (2021): Research on landscape design system based on 3D virtual reality and image processing technology. – Ecological Informatics 9(7): 101287-101299.
[37] Soltani Firouz, M., Sardari, H. (2022): Defect detection in fruit and vegetables by using machine vision systems and image processing. – Food Engineering Reviews 14(3): 353-379.
[38] Song, L., Wang, H., Chen, P. (2020): Automatic patrol and inspection method for machinery diagnosis robot-sound signal-based fuzzy search approach. – IEEE Sensors Journal 20(15): 8276-8286.
[39] Sun, Z., Wang, X., Wang, Z., Yang, L., Xie, Y., Huang, Y. (2021): UAVs as remote sensing platforms in plant ecology: Review of applications and challenges. – Journal of Plant Ecology 14(6): 1003-1023.
[40] Sun, X., Wang, P., Wang, C., Liu, Y., Fu, K. (2021): PBNet: Part-based convolutional neural network for complex composite object detection in remote sensing imagery. – ISPRS Journal of Photogrammetry and Remote Sensing 173(1): 50-65.
[41] Syriopoulos, T., Tsatsaronis, M., Karamanos, I. (2021): Support vector machine algorithms: An application to ship price forecasting. – Computational Economics 57(1): 55-87.
[42] Tesfamikael, H. H., Fray, A., Mengsteab, I., Semere, A. (2021): Simulation of eye tracking control based electric wheelchair construction by image segmentation algorithm. – Journal of Innovative Image Processing (JIIP) 3(1): 21-35.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084

[43] Wang, M. (2021): Investigation of remote sensing image and big data analytic for urban garden landscape design and environmental planning. – Arabian Journal of Geosciences 14(24): 1-14.
[44] Wang, J., Gu, H., Chen, B., Gu, C., Zhang, Q., Xing, Z. (2021): A spatio-temporal dam deformation zoning method considering non-uniform distribution of monitoring information. – IEEE Access 9: 117615-117628.
[45] Wang, L. Y., He, Y. P. (2023): Environmental landscape art design based on visual neural network model in rural construction. – Ecological Chemistry and Engineering S 30(2): 267-274.
[46] Wang, Z., Rosen, D. (2023): Manufacturing process classification based on heat kernel signature and convolutional neural networks. – Journal of Intelligent Manufacturing 34(8): 3389-3411.
[47] Wei, Y., Zeng, A., Zhang, X., Huang, H. (2022): RAG-Net: ResNet-50 attention gate network for accurate iris segmentation. – IET Image Processing 16(11): 3057-3066.
[48] Yao, L., Hu, D., Zhao, C., Yang, Z., Zhang, Z. (2021): Wireless positioning and path tracking for a mobile platform in greenhouse. – International Journal of Agricultural and Biological Engineering 14(1): 216-223.
[49] Yu, W., Li, S. (2024): Remote sensing enabled sustainable tomato plant health and pest surveillance using machine learning techniques. – International Journal of Sensor Networks 44(4): 237-248.
[50] Zuo, Z., Tong, X., Wei, J., Su, S., Wu, P., Guo, R., Sun, B. (2022): AFFPN: Attention fusion feature pyramid network for small infrared target detection. – Remote Sensing 4(14): 3412-3413.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_20592084