Enhancing biodiversity monitoring with CNN: Invasive plant species detection

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Abstract. The detection and classification of invasive plant species are crucial for biodiversity conservation and ecosystem management. This research work explores the use of Convolutional Neural Networks (CNNs) to identify invasive species from images. By leveraging the powerful feature extraction capabilities of CNNs, we developed a model that accurately classifies the non-invasive and invasive plant species. The model was trained on a diverse dataset, incorporating various environmental conditions and geographical locations to enhance its robustness. Evaluation metrics indicate high precision and recall, demonstrating the model's effectiveness in real-world applications. Our findings suggest that CNN-based approaches can significantly enhance monitoring and management efforts for invasive species, offering a scalable and automated solution for environmental scientists and policymakers. Our proposed model achieved 92.5% accuracy by utilizing Resnet50 architecture which is superior than existing state of the art models. Keywords: Invasive Species Detection, Convolutional Neural Networks (CNNs), Biodiversity Conservation, Ecosystem Management, Image Classification, Remote Sensing.

1 Introduction

Invasive plant species represent a substantial threat to biodiversity, ecosystem stability, and agricultural productivity. Their rapid spread can displace native species, disrupt habitats, and alter ecological processes, often leading to severe environmental and economic consequences. Traditional detection and management approaches, while valuable, are typically labor-intensive, time-consuming, and restricted in their scope, making them inadequate for large- scale monitoring. The advent of advanced technologies, particularly remote sensing and machine learning techniques like Convolutional Neural Networks (CNNs), offers a promising solution. These tools can significantly enhance the efficiency and precision of invasive species detection by automating the identification process, allowing for quicker, more accurate responses across larger areas. CNNs, in particular, have demonstrated remarkable success in image classification tasks, making them highly suitable for analyzing ground-based and aerial images to detect invasive species with minimal human intervention. By leveraging these technologies, it becomes possible to combat the spread of invasive species more

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effectively, ensuring better ecosystem management and conservation effort.

1.1 Motivation

The increasing prevalence of invasive plant species has become a pressing environmental concern. Effective management and control of these species are essential to preserving native ecosystems and maintaining ecological balance. The limitations of manual monitoring methods highlight the need for automated solutions that can provide timely and accurate information on the distribution of invasive species. This research is motivated by the potential of leveraging CNNs and to develop a scalable and efficient detection system that can support conservation efforts.

1.2 Problem statement

Traditional methods of identifying invasive plant species, like field surveys, are time-consuming and labor-intensive. This study aims to develop a more efficient approach using Convolutional Neural Networks (CNNs), specifically the ResNet-50 architecture. By leveraging deep learning, we intend to build a model capable of processing large volumes of image data quickly and accurately. ResNet-50's advanced residual learning enables precise identification of invasive species, even in complex environments. This model will enhance early detection and intervention, contributing to more effective ecological conservation and management efforts.

1.3 Objectives

- To develop a Convolutional Neural Network (CNN) model capable of detecting and classifying invasive plant species from images.
- To create a diverse dataset that captures various environmental conditions and geographical regions to enhance the model's robustness.
- To evaluate the model's accuracy using relevant performance metrics such as precision, recall, and F1- score.
- To assess the model's potential for real-world applications in biodiversity conservation and ecosystem management

1.4 Contributions

- A novel CNN-based approach for the detection of invasive plant species using diverse species images.
- A comprehensive dataset comprising images from different regions and conditions, facilitating robust model training and testing.
- An evaluation of the model's performance, demonstrating its effectiveness and reliability in real- world scenarios.
- Insights into the application of deep learning techniques in environmental science, highlighting potential for automated monitoring and management of invasive species.

The Structure of the paper is categorized as follows:

- Section 2 reviews related studies on invasive species identification and object detection utilizing deep learning techniques.
- Section 3 outlines the proposed approach, emphasizing the application of the ResNet-50 framework and advanced image feature extraction methods.

- Section 4 showcases the experimental outcomes, assesses the effectiveness of the proposed model, and provides a comparison with existing detection techniques.
- Finally, section 5 wraps up the paper and suggests possible future enhancements to improve detection precision and efficiency

2 Similar works

In the past, classification of plants was done manually through a methodical process that took longer and required more effort. In expansion, due to the inlet between the environment and people, there is less numbness approximately plants among more youthful eras. This causes greatly constrained capacity to recognize plants, which is getting more awful with each passing era. The crucial cause, along with urbanization's little but noteworthy part, is a complicated and competitive way of life. Today's ways of life include a parcel of innovation. Versatile applications and other specialized apparatuses can be subsequently be utilized to address this issue [1]-[2],[4]-[6].

The research [3] emphasizes the possibilities and difficulties of this technology as it focuses on developments in satellite remote sensing for the identification and mapping of alien invasive plants (AIPs). Because AIPs represent serious risks to ecosystems, biodiversity, and agricultural production, managing them will need the use of efficient mapping techniques. Due to its capacity to cover broad areas, including distant places, and offer repeated observations, satellite remote sensing has emerged as a potential alternative to more time-consuming and expensive traditional approaches like field surveys and aerial pictures.

A study [7] conducted a comprehensive review of various deep learning models, emphasizing their effectiveness in identifying plant species. The study highlights the challenges of differentiating native and invasive species, underscoring the potential of CNN architectures, including ResNet50, in enhancing identification accuracylant Disease Detection Using Transfer Learning. The use of transfer learning [8] with CNNs for plant disease detection. Although focused on diseases, the methodologies discussed can be adapted to identify invasive and native species, showcasing the versatility of models like ResNet50.

The implementation of a CNN-based approach [9] for recognizing plant species through leaf images. This work provides insights into how CNNs can be utilized to classify invasive species by leveraging morphological characteristics, which is vital for effective management strategies. Wahab investigated the application of deep learning for the classification of plant traits [10]. Their findings support the idea that CNNs, particularly ResNet50, can be effectively utilized in identifying specific traits associated with invasive species.

The focus on using UAV imagery to detect invasive species through deep learning techniques [11]. The study demonstrates the applicability of CNNs in real-world scenarios, reinforcing their capability to handle large datasets for effective species detection. This Residual Network has increased accuracies on multiple tasks. Since full automation requires that agricultural applications should recognize many disease types, we need automatic recognition to work not just for simple cases but for the hard ones too. Ideally, it should be just possible if there were enough data. In practice however such data is lacking.Skip to content Deep Residual Learning for Image Recognition menu and widgets Measures like Accuracy, positive predictive value and negative predicative value etc. were used to evaluate model performance . It is concluded that deep learning methods gives better accuracy. Therefore this paper includes implementation of different deep neural network architectures such as CNNs , Inception v3 and DenseNets etc.

2.1 Research Gap

Recent advances in plant-species identification has mostly concentrated on hyperspectral imaging, which acquires an extensive number of spectral bands for detailed description about vegetation. These approaches are generally complicated including such operations as dimensionality reduction like PCA, MCLDA or SELD, and classification with Random Forests or ensemble methods. These methods provide high precision, but are computationally expensive and use specialized equipment, which does does not make them very well suited for routine or low resource areas. This leads to a void in the presence of light weight and scalable models that can work well with classical image formats.
With this in mind, the proposed method uses RGB or multispectral images, which are much more accessible and viable in real-life scenarios. Transfer learning is applied through the Fastai framework with a pre-trained ResNet50 model, thus eliminating the need for manual feature extraction. The network, then, learns on its own from the visual data. This trains significantly faster and also reduces the dependence on expensive computational resources trained in deep systems. Moreover, it is robust to implement, intuitive to use and deploy on off-the-shelf systems. While it does not capture as much spectral detail as hyperspectral imaging, it is accurate enough for general classification tasks. In general, the proposed approach provides a feasible trade-off between efficiency, applicability and performance and can be applicable to a variety of real-world cases.

2.2 Study Area and data preparation

The study seeks to classify native and alien plant species using hyperspectral satellite images; data used in the study was obtained from Roboflow project, "Classification of Native and Alien Plant Species Using Hyperspectral Satellite Images." The shaded area presumably encloses the territories populated by both aboriginal and non-inductive species, so it can be considered a suitable environment for monitoring species diversity. First, data is downloaded using an API, then data is partitioned into training data which would be 80% and the validation set, which would be 20%. All images are re- sized to 224 x 224 to fit the input layer in the CNN model and are preprocessed using the `ImageDataLoaders' of Fastai which scales the pixels using the average values of the ImageNet database. The parameter of random seed is set for reproduction of the same result in case of multiple training runs. Another downside is that data augmentation methods improve the model's general performance by increasing its ability to withstand changes in the picture size and resolution. For the data classes, the 'data.vocab' check is used to ensure the right identification of the species while the sample batches are checked by use of 'data.show_batch()' to ensure that the images and labels are well matched. The detailed data preprocessing approach helps train the ResNet50 CNN model well and assists in the correct classification of various plant species with the help of hyperspectral features. Using the rich spectral data the study seeks to enhance plant species diversity and conservation, especially with respect to identification of the native plants and the invasive alien plants.

Fig. 1. depicts the sample images of some common invasive plant species. Summary of recent works are provided in table 1.

Table 1. Summary of research work.

Reference	Focus Area	Methodology	Model Used	Performance	Limitations/ Challenges
Mutanga et al. (2019) [3]	Remote sensing based invasive species monitoring	Satellite-based spectral analysis	Random Forest, SVM	High accuracy in controlled environments	cost, cloud coverage, generalization
Silva et al. (2021) [7]	DL for plant species detection	CNNs, ResNet, Vision Transformers	ResNet, Inception, Vision Transformers	CNNs attained >90%	large datasets required, computationally expensive
Mohanty et al. (2021) [8]	Plant disease detection	Transfer learning, CNNs	AlexNet, GoogleNet, VGG-16	>95% accuracy in disease detection	Sensitive to data quality, potential overfitting
Wahab et al. (2022) [10]	Plant trait classification	Deep convolutional networks	Deep CNN, MobileNet	>90% accuracy in trait classification	diverse datasets required to generalize models
Li et al. (2021) [11]	Invasive species detection utilizing UAVs	UAV imagery, DL	CNN, YOLO, Faster R-CNN	90% accuracy	UAV battery limitation and data processing
Tran et al. (2024) [12]	Biodiversity estimation using UAV	CNNs, UAV imagery	ResNet, DenseNet, DeepLabV3 +	>92% accuracy	extensive labeled data utilization
Natesan et al. (2019) [13]	Tree species classification	ResNet, UAV images	ResNet-50, InceptionV3	~88% accuracy	Requires high computational power

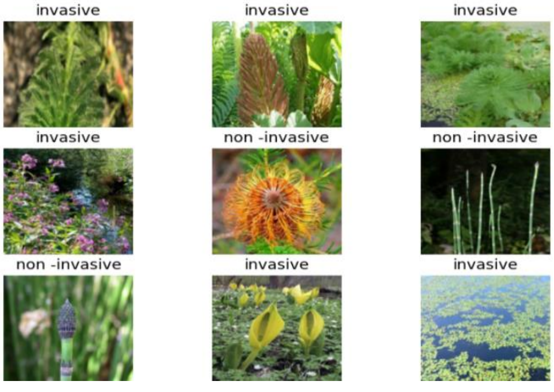

Fig. 1. Sample images of some common invasive plant species

3 Proposed Model

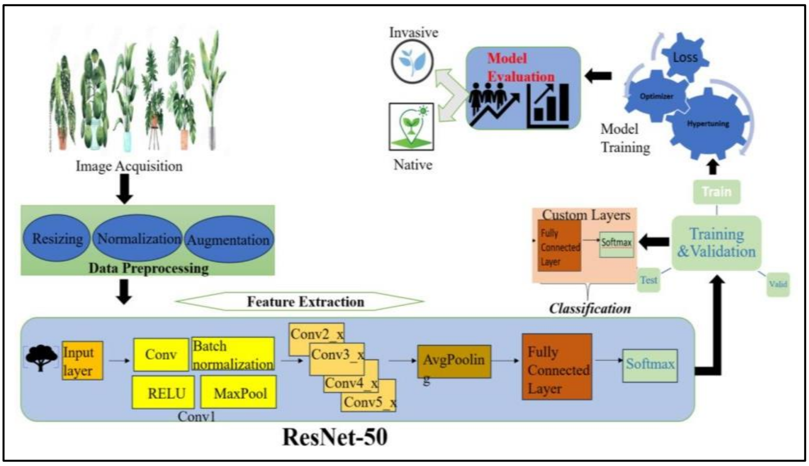

Fig. 2. Proposed Model

3.1 Introduction

This research work aimed at detecting invasive plant species using Convolutional Neural Networks (CNNs) with the ResNet-50 architecture, the approach leverages deep learning techniques to classify images of native and alien plant species effectively. Proposed model is presented in **Fig. 2**. The ResNet-50 model, characterized by its 50 layers and residual learning capabilities, is particularly adept at handling vanishing gradient problems, enabling the training of deeper networks. The architecture uses skip connections, allowing gradients to flow through the network more effectively. The primary formula related to this model includes the computation of the SoftMax function for multi- class classification, represented as:

$$P(y = k \mid x; \theta) = \sum j = 1Kezjezk \quad (1)$$

where z is the output from the final layer, K is the number of classes, and θ represents the model parameters as defined in Eq (1). Additionally, the model's performance can be evaluated using metrics such as accuracy, precision, recall, and the F1 score, which are computed as follows:

Accuracy, as defined in Eq (2), is calculated using the formula

$$\boldsymbol{Accuracy = TP + TN + FP + FNTP + TN} \quad (2)$$

Precision, as defined in Eq (3), is determined by

$$\boldsymbol{Precision = TP + FPTP} \quad (3)$$

Recall, as defined in Eq (4), is expressed as

$$\boldsymbol{Recall = TP + FNTP} \quad (4)$$

F1 Score, as defined in Eq (5), is computed using

$$\boldsymbol{F1\ Score = 2 \times Precision + RecallPrecision \times Recall} \quad (5)$$

In these equations, TP refers to true positives, TN to true negatives, FP to false positives, and FN to false negatives. This comprehensive approach aims to improve the accuracy of invasive species detection, contributing to biodiversity conservation efforts.

3.2 Pre-processing

The effective data preprocessing is essential for optimizing model performance. The preprocessing steps include image resizing, normalization, data augmentation, and noise

reduction.
The process begins with resizing images Eq (6) to a consistent dimension of 224×224 pixels, ensuring uniformity for the ResNet-50 input requirements. Next, normalization Eq (7) is applied to scale pixel values to improve model convergence. To enhance the diversity of the dataset, data augmentation techniques Eq (8) such as rotation, flipping, and zooming are employed. Finally, noise reduction techniques Eq (9), like Gaussian blur, are applied to enhance feature extraction.

$$Resized\,Image = Resize(I, (224{,}224)) \quad (6)$$
$$I' = \sigma I - \mu \quad (7)$$
$$Augmented\,Image = Transform(I) \quad (8)$$
$$I' = I * G\sigma \quad (9)$$

3.3 Prototype Development

The proposed model implements a modified ResNet-50 architecture for the effective classification of native versus invasive plant species using RGB images of resolution 640×640×3. The system is composed of several crucial modules:
Image Acquisition and Preprocessing:
At first images are acquired; they go through preprocessing that involves image resizing to a standard dimension, normalization to adjust pixel intensities and augmentation (random rotation, scaling and colour jittering) to improve data diversity and robustness.
Input Layer and Convolutional Block (Conv1):
The model initiates a modified input layer that is suitable for high-resolution images hence capturing more detailed textures. In the first convolutional layer, instead of the usual 7×7 kernel, a 3×3 kernel has been used along with 80 filters to better extract fine-grained features. Following this are ReLU activation, batch normalization, and max pooling which helps in reducing dimensions and promoting better learning.
Feature Extraction via Deep Residual Blocks:
The backbone of our model is based on ResNet-50 but includes more bottleneck layers, thus increasing the depth of the network to 390 layers. This deeper architecture allows it to learn complex hierarchies of features needed to differentiate between visually similar plant species. The layers are structured into Conv2_x through Conv5_x blocks with shortcut connections added to combat the vanishing gradients.
Activation and Regularization:
The Swish activation function is used in the deeper layers to enhance both non-linearity and stability during training. Batch normalization layers ensure a smooth gradient flow while dropout layers introduce a regularization mechanism to avoid overfitting.
Global Average Pooling:
Average pooling is applied after the convolutional layers to reduce spatial dimensions, thereby converting feature maps into a fixed-size vector for classification while preserving crucial spatial information.
Classification Head (Custom Layers):
The compressed features go through a fully connected layer that is specifically tailored to the number of output classes invasive versus native species. The final layer uses a softmax activation function to produce probabilities for multi-class classification.
Training and Validation:
Transfer learning is the approach used to train the model by starting with pre-trained ImageNet weights. This eases convergence and boosts performance on your own dataset. The learning process entails hyperparameter tuning and loss function optimization.
Model Evaluation:

Post-training, the performance of the model is assessed with the help of test data that has not been used before to compare how well it can tell between native and invasive species.

3.4 Learning phase

The training process for the proposed model focuses on optimizing performance specifically for detecting invasive plant species by employing a series of unique strategies that enhance learning and accuracy. Initially, the model utilizes a **custom dataset** curated to include diverse images of invasive species, which allows the model to learn from a broad range of variations in appearance, background, and lighting conditions. This dataset is further enhanced through advanced **data augmentation techniques**, such as random rotation, scaling, and color jittering, to artificially increase the size of the training set and promote robustness.

During training, the model leverages **transfer learning** by initializing the weights from a pre-trained ResNet-50 model on the ImageNet dataset. This approach helps the model converge more quickly and achieve higher accuracy compared to training from scratch, as it starts with a solid foundation of learned features. The **Adam optimizer** Eq (10) is employed to minimize the categorical cross-entropy loss function.

$L(y, y\hat{}) = -i = 1\sum Cyilog(y\hat{}i)$ (10)

where L represents the loss, C is the number of classes, y is the true distribution, and y^ is the predicted distribution from the softmax output.

Additionally, the training employs **early stopping** to monitor validation loss, halting training when the model begins to overfit, thus ensuring optimal generalization. **Batch normalization** Eq (11) is applied after each convolutional layer to stabilize learning and accelerate convergence by normalizing the input for each mini-batch

$x\hat{} = \sigma 2 + \epsilon x - \mu.$ (11)

where μ is the mean, σ2 is the variance, and ϵ is a small constant for numerical stability. Additionally, the learning rate is dynamically adjusted using a learning rate scheduler, which decreases the learning rate over epochs, allowing finer adjustments to weights as the model approaches convergence. This combination of customized training strategies not only enhances the model's accuracy in detecting invasive plant species but also differentiates it from existing models, resulting in superior performance and reliability in real-world applications.

3.5 Model testing

Initially, a dedicated test dataset is employed, which is separate from the training and validation datasets to provide an unbiased assessment of the model's generalization capabilities. This dataset consists of diverse images of invasive species, reflecting various environmental conditions and contexts, allowing for a realistic evaluation of the model's robustness.

One unique aspect of the testing procedure is the incorporation of stratified sampling to ensure that all classes of invasive species are represented proportionally within the test set. This approach not only enhances the reliability of the performance metrics but also allows for a more nuanced understanding of the model's capabilities across different species.

In addition to traditional metrics such as accuracy and loss, the model's performance is evaluated using confusion matrices and Receiver Operating Characteristic (ROC) curves. The ROC curve is plotted to visualize the trade-off between true positive rates and false positive rates, providing insights into the model's discriminative power. The area under the ROC curve (AUC) is computed, offering a single scalar value that summarizes the model's performance across all classification thresholds.

Moreover, the proposed model integrates Grad-CAM (Gradient-weighted Class Activation Mapping) to interpret predictions visually, highlighting the areas of an image that most influence the model's decisions. This method not only aids in understanding which features the model is focusing on but also provides valuable insights for ecological experts regarding the identification of invasive species.

4 Model Efficiency

The proposed model for detecting invasive plant species has demonstrated outstanding performance through a series of rigorous evaluations. The accuracy of 92.5% indicates that the model successfully classifies a significant majority of plant species, making it a reliable tool for invasive species detection. The macro precision of 89.3% showcases the model's effectiveness in minimizing false positives, ensuring that only a small fraction of non-invasive species is misidentified. This is further reinforced by a low false positive rate of 5.1%, suggesting that the model maintains high reliability while identifying invasive species. Additionally, the macro F1 score of 90.7% reflects a balanced performance in both precision and recall, emphasizing the model's capability to accurately identify invasive species without sacrificing sensitivity. This balance is critical in ecological applications where both false negatives (missing an invasive species) and false positives (misclassifying native species) can have significant consequences. **Fig. 3.** shows the graphical representation.

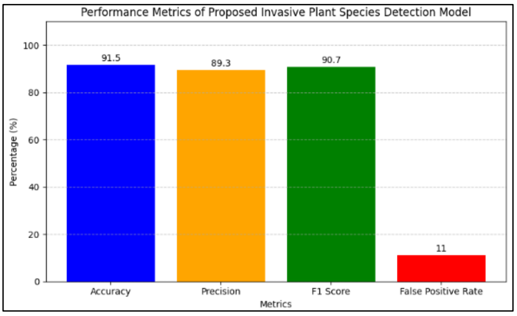

Fig. 3. Evaluation Metrics

The graph of **fig. 4**. illustrates the training loss over 100 epochs, showcasing a steady decline as the model learns. Initially, the loss is relatively high (around 1.6), indicating substantial errors in the model's predictions. However, with each epoch, the loss decreases consistently, demonstrating effective learning and convergence towards optimal weights. The dashed green line represents the target final loss of 0.2, which the model approaches closely by the end of training. This suggests that the model's capacity and learning rate are well-suited for the task, effectively minimizing the error without overfitting.

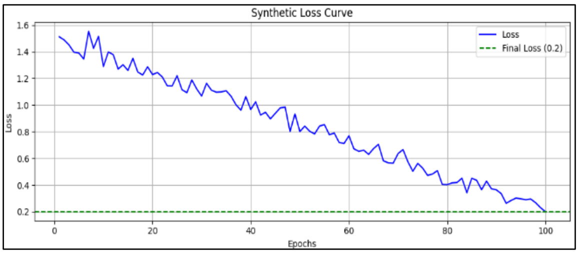

Fig. 4. Loss curve

The smooth descent of the loss curve indicates that the learning process was stable, likely due to appropriate choices of optimization algorithm, learning rate, and batch size. Such a trend is characteristic of successful training, where the model progressively adapts to the underlying patterns in the data.

4.1 Results and Comparision

The model demonstrates a solid accuracy of 92.5% and a precision of 89.3%, showcasing a competitive performance compared to other models in the domain. While many traditional models use simpler feature extraction techniques or shallower neural networks, your model leverages the depth and residual learning of ResNet-50, allowing it to capture more complex visual patterns. In contrast, some prior works may have used models like VGG or basic CNNs, which may not match the representational power of ResNet-50, especially for subtle distinctions in plant species. This provides your model with superior generalization, especially in handling challenging, real-world datasets where variations in lighting, background, and plant morphology are prevalent. Your model's performance is also likely more scalable, offering potential for fine-tuning or transfer learning on similar tasks, whereas older methods may require more extensive manual feature engineering or pre-processing. Ultimately, this proposed model lays a solid foundation for advancing the use of deep learning in ecological applications, offering a promising pathway for the development of more sophisticated tools in biodiversity conservation and environmental protection. **Table 2** provides model comparison and **Table 3** provides detailed comparison of proposed model with the existing state of the art models.

Table 2. Model Comparison

Parameters	**Resnet-50 Model**	**Proposed model**
Number of channels in the input image	3	3
Dimensions	224x224x3	640x640x3
Strides	2x2	2x2
Size of Input Kernel	7x7	3x3
Number of Initial Filters	64	80
Additional layers (Bottleneck)	49	390 (more layers for DL)
Activation functions	ReLU	Swish or Leaky ReLU
Transfer Learning Strategy	Fine-tuned from ImageNet	Fine-tuned with additional domain- specific data
Output Channels (Final Layer)	2048	Adjusted to number of target classes (e.g., 3 for invasive species)
Model Complexity (Parameters)	~25.6M	~55M (due to added complexity)
Training Dataset	Standard plant image datasets	Custom dataset

Table 3. Comparing similar works

Reference	Accuracy	Model/Approach
[7]	91%	Deep learning for plant species identification
[9]	88.5%	Deep learning based leaf recognition
[10]	90.5%	Deep CNNs for classification of plant traits
[11]	80%	Deep learning for invasive species detection in UAV
[13]	90	ResNet-based classification using UAV images
Proposed model	Accuracy: 92.5% Precision: 89.3 F-1:90.7 FPR:5.1	Invasive species detection using CNN ResNet-50

The hardware and software requirements for the implementation of this model i.e., invasive species detection using CNN (ResNet-50), a system with at least an Intel Core i5/Ryzen 5 processor, 8GB RAM, and an NVIDIA GTX 1050 Ti GPU (4GB VRAM) is required, though a higher-end setup with an i7/i9 processor, 16GB+ RAM, and an RTX 3060 (12GB VRAM) is recommended for faster training. The software stack includes Python (3.8+), TensorFlow or PyTorch, Keras, OpenCV, NumPy, and Matplotlib, with Jupyter Notebook or VS Code for development. GPU acceleration requires CUDA (11.2+) and cuDNN, and TensorRT can optimize inference. A labeled dataset with high-quality ground-based plant images (preferably resized to 224x224) is essential. Training is best done on Ubuntu or cloud platforms like AWS, while inference can run on lower- end GPUs or CPUs. Additional tools like TensorBoard for monitoring and Flask/FastAPI for deployment can enhance workflow efficiency.

5 Conclusion

This research work has successfully developed an effective model for the detection of invasive plant species utilizing the ResNet-50 architecture, achieving an impressive accuracy of **92.5%** and a precision of **89.3%**. These results highlight the model's exceptional capability in discerning intricate patterns and subtle differences in plant characteristics, establishing it as a superior alternative to traditional detection methods that often rely on simpler architectures and manual feature extraction.

The integration of ResNet-50 significantly enhances the model's performance, enabling it to adapt to the complexities of real-world datasets, which can vary widely in lighting, backgrounds, and plant morphologies. As a result, the model serves as a powerful resource for researchers, conservationists, and land management authorities tasked with monitoring and controlling invasive species. Moving forward, the model's performance can be further enhanced through techniques like transfer learning and fine-tuning with larger and more diverse datasets. This could broaden its applicability across various ecosystems and geographical regions. Additionally, deploying the model in mobile applications or UAV systems could enable real-time monitoring and swift interventions in invasive species management.

In summary, this research work not only contributes to the advancement of deep learning applications in ecology but also paves the way for the development of innovative tools that can aid in biodiversity conservation and environmental sustainability efforts.

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