LatIA. 2024; 2:15
doi: 10.62486/latia202415
ISSN: 3046-403X

ORIGINAL

Development of an Image Recognition System Based on Neural Networks for the Classification of Plant Species in the Amazon Rainforest, Peru, 2024

Desarrollo de un Sistema de Reconocimiento de Imágenes Basado en Redes Neuronales para la Clasificación de Especies de Plantas en la Selva Amazónica, Perú, 2024

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Citar como: Meneses Claudio BA. Development of an Image Recognition System Based on Neural Networks for the Classification of Plant Species in the Amazon Rainforest, Peru, 2024. LatIA. 2024; 2:15. https://doi.org/10.62486/latia202415

Enviado: 28-07-2023 **Revisado:** 03-11-2023 **Aceptado:** 10-01-2024 **Publicado:** 11-01-2024

Editor: Prof. Dr. Javier González Argote

ABSTRACT

Introduction: the recognition and classification of plant species in the Amazon Rainforest is crucial for biodiversity conservation and ecological research. This study presents the development of an image recognition system based on neural networks for the classification of plant species in the Amazon Rainforest, Peru, 2024.
Objective: create an efficient model that can identify and classify various plant species from images, thus improving current methods of cataloging and studying Amazonian flora.
Method: the methodology includes collecting a large dataset of plant images, followed by rigorous preprocessing to normalize and augment the data. A convolutional neural network (CNN) was designed and trained using advanced machine learning techniques, and its performance was evaluated using metrics such as precision, recall and F1-score.
Results: the results show that the developed model achieves an accuracy of 92 %, surpassing traditional methods and some previous models in the literature. This high precision suggests that the system can be a valuable tool for researchers and conservationists in the Amazon Rainforest.
Conclusions: this study demonstrates the effectiveness of neural networks in the classification of plant species and highlights their potential to contribute significantly to the conservation and study of biodiversity in the Amazon region.

Keywords: Image Recognition; Neural Networks; Plant Classification; Amazon Rainforest; Biodiversity Conservation.

RESUMEN

Introducción: el reconocimiento y clasificación de especies de plantas en la Selva Amazónica es crucial para la conservación de la biodiversidad y la investigación ecológica. Este estudio presenta el desarrollo de un sistema de reconocimiento de imágenes basado en redes neuronales para la clasificación de especies de plantas en la Selva Amazónica, Peru, 2024.
Objetivo: crear un modelo eficiente que pueda identificar y clasificar diversas especies de plantas a partir de imágenes, mejorando así los métodos actuales de catalogación y estudio de la flora amazónica.
Método: la metodología incluye la recolección de un conjunto de datos amplio de imágenes de plantas, seguido de un preprocesamiento riguroso para normalizar y aumentar los datos. Se diseñó y entrenó una red neuronal convolucional (CNN) utilizando técnicas avanzadas de machine learning, y se evaluó su rendimiento mediante métricas como precisión, recall y F1-score.
Resultados: los resultados muestran que el modelo desarrollado alcanza una precisión del 92 %, superando los métodos tradicionales y algunos modelos previos en la literatura. Esta alta precisión sugiere que el

sistema puede ser una herramienta valiosa para investigadores y conservacionistas en la Selva Amazónica.
Conclusiones: en conclusión, este estudio demuestra la eficacia de las redes neuronales en la clasificación de especies de plantas y destaca su potencial para contribuir significativamente a la conservación y estudio de la biodiversidad en la región amazónica.

Palabras clave: Reconocimiento de Imágenes; Redes Neuronales; Clasificación de Plantas; Selva Amazónica; Conservación de Biodiversidad.

INTRODUCTION

The Amazon rainforest, one of the world's most biodiverse ecosystems, is home to approximately 16 000 plant species. However, deforestation and climate change are threatening this biodiversity at an alarming rate. According to the World Resources Institute, the Amazon lost around 2,3 million hectares of forest cover by 2020. This habitat loss affects plants, wildlife, and indigenous peoples who depend on this ecosystem for survival. Accurate and rapid plant species classification is crucial for conserving this ecosystem. However, traditional methods are laborious and require botanical experts, limiting the ability to respond to these threats. Furthermore, it is estimated that only 15 % of the Amazonian flora has been formally described, underscoring the urgent need for practical tools for its identification and conservation.(1)

Globally, deforestation has contributed significantly to biodiversity loss. According to FAO, between 2015 and 2020, the world lost approximately 10 million hectares of forest per year, the equivalent of an area the size of Iceland. The Amazon region has been one of the hardest hit, with a deforestation rate accounting for about 30 % of annual global deforestation. In addition, Amazon stores around 123 billion tons of carbon, making it a crucial element in regulating the global climate. The loss of this forest cover affects local biodiversity and has important implications for global climate change.(2)

Peru's neighboring countries, such as Brazil, Colombia, Bolivia, Ecuador, and Chile, face a similar situation. Brazil, which contains 60 % of the Amazon rainforest, lost more than 1,5 million hectares of forest by 2020, making it the country with the highest deforestation rate in the region.(3) In Colombia, it is estimated that the Amazon represents approximately 42 % of the national territory and is also threatened by illegal activities and agricultural expansion.(4) In 2020, Colombia lost about 159,000 hectares of Amazon forest. Bolivia, which holds 8 % of the Amazon, has experienced increased deforestation due to agriculture and cattle ranching, losing approximately 200,000 hectares of forest in 2019.(5) Ecuador, home to about 2 % of the Amazon, has experienced significant deforestation with losses of up to 100,000 hectares annually due to oil exploitation and agricultural expansion. Although Chile does not share the Amazon, it faces conservation challenges in other biomes, such as the temperate Valdivian forest, where illegal logging and forest fires are critical problems.(6)

Peru has about 13 % of the Amazon, with a wealth of flora. However, according to Peru's Ministry of Environment, the country loses approximately 150 000 hectares of Amazon forest annually due to illegal logging and mining. This rate of deforestation places Peru among the countries with the highest forest losses in the Amazon region. In addition, the need for efficient biodiversity identification and monitoring tools exacerbates this problem, hindering conservation and scientific study efforts. Recent studies indicate that around 25 000 plant species have been identified in Peru, many of which are endemic and in danger of extinction due to habitat loss.(7)

The theoretical framework of this study is based on several vital theories and technologies. Convolutional neural networks (CNNs) are highly effective in image recognition. CNNs are a deep neural network that uses convolutional layers to extract image features, enabling highly accurate object identification and classification.(8) This approach is fundamental to the development of automated plant species classification systems. Machine learning is a branch of artificial intelligence that allows systems to learn and improve from data without being explicitly programmed. In plant classification, machine learning enables the development of models that can generalize and recognize patterns in images of new species not seen during training.(9)

Biodiversity conservation is a discipline that seeks to protect biological diversity at the genetic, species, and ecosystem levels. Accurate and rapid species identification is a crucial component of conservation programs, as it allows for monitoring changes in biodiversity and taking preventive measures to protect threatened species.(10) Image recognition has found applications in various fields, from medicine to agriculture. In the field of biodiversity, it has been used to identify animal and plant species, which facilitates the work of researchers and conservationists by providing automated tools for the classification and study of flora and fauna.(11)

In summary, this study is based on integrating convolutional neural networks and machine learning techniques to develop an efficient and accurate image recognition system to classify plant species in the Peruvian Amazon Rainforest, contributing significantly to conservation efforts and scientific study in the region.

Literature review

Plant species distribution is essential for nature conservation, agriculture, and forestry. However, obtaining accurate data to map these species is often a laborious process that requires a large amount of training data, usually derived from intensive field surveys or visual interpretation of remotely sensed images. The main objective of this study is to overcome the limitations of simple labels provided by citizen science reconnaissance platforms and use them to train advanced pattern models that enable accurate segmentation of plant species in UAV imagery. The proposed approach is divided into two phases. In the first phase, image classification models based on convolutional neural networks (CNNs) are trained using the simple labels of photographs obtained from citizen science platforms. Then, these models are applied in a moving window approach on UAV orthoimages to create segmentation masks. In the second phase, these segmentation masks train CNN-based image segmentation models with an encoder-decoder structure. The method was tested on UAV orthoimages acquired in summer and autumn at a test site with ten temperate deciduous tree species in different mixtures. The results show that several tree species can be mapped with surprising accuracy, with an average F1 score of 0,47. In inhomogeneous species sets, the accuracy increased significantly, reaching an average F1 score of 0,55. In addition, the study revealed that variability in citizen science photographs, in terms of acquisition date and context, facilitates the generation of transferable models throughout the vegetation season. The study concludes that citizen science data can significantly improve our ability to monitor hundreds of plant species and, thus, the planet's biodiversity across space and time. Using simple citizen science photographs and tags allows the creation of accurate plant species segmentation models without generating new training data, representing a significant advance in the efficiency and effectiveness of biodiversity monitoring. (12)

On the other hand, author Cheng et al. (2024) state that accurate identification of weeds in rice fields is crucial for agriculture but is hampered by factors such as shading of rice plants, algal interference in fields, and weeds with small targets. These adverse conditions hinder accurate and effective weed detection, negatively affecting agricultural productivity. This study aims to improve weed recognition using combined deep learning techniques to reduce negative influencing factors and increase model accuracy and speed in complex rice field environments. To improve model training and generalization capability, data augmentation of weed sample data was used to reduce overfitting. Improved image quality in complex environments was achieved by introducing MSRCP (Multi-Scale Retinex with Color Preservation). Weed target recognition was performed on low contrast and low clarity rice field images by forward segmentation and classification with ViT (transformer vision) on HD images. Loss of information in the network compression process was avoided, and small targets were retained in HD images. The YOLOv7 model was replaced by the lightweight GhostNet network, which was integrated with the CA attention mechanism to reduce the number of parameters and computations, improving feature extraction and real-time performance of weed recognition. Experimental results showed that expanding the weed dataset improved model accuracy. The ablation test revealed that the average accuracy of the test set after data augmentation was 84,9 %, outperforming the model trained on the original dataset by 10,8 percentage points. The ViT classification network outperformed Resnet 50 and Vgg regarding accuracy, recall, and detection speed, increasing accuracy by 7,9 and 7,5 percentage points, respectively, and recall by 7,1 and 5,3 percentage points, respectively. The average accuracy of the enhanced YOLOv7 model was 88,2 %, outperforming the original model by 3,3 percentage points, with a reduction of 10,43 million parameters and $66,54 \times 10^9$ operations per second. The average accuracy of the improved model increased by 2,6 percentage points after image enhancement with MSRCP before recognition. In complex environments, the average accuracy of the enhanced ViT-YOLOv7 model was 92,6 %, outperforming the YOLOv5s, YOLOXs, MobilenetV3-YOLOv7, enhanced YOLOv7, and YOLOv8 models by 11,6, 10,1, 5,0, 4,2, and 4,4 percentage points, respectively. The study concludes that the combination of advanced deep learning techniques, such as ViT classification and GhostNet lightweight network, significantly improves the accuracy and speed of weed recognition in complex agricultural environments. The integration of MSRCP and data augmentation enables better detection in adverse conditions, thus contributing to more effective weed identification and optimization of agricultural production. (13)

Research by Park et al. (2024) states that the application of artificial intelligence (AI) and intense learning in the analysis of X-ray images of plant and animal items in quarantine presents significant challenges due to the variability in the shape, density, and arrangement of the scanned items. Accurate identification and classification of these elements are crucial to improve inspection and quarantine processes, but traditional techniques often merely detect the presence of these elements without providing detailed classification. This study aims to develop and validate a convolutional neural network (CNN) model capable of classifying and identifying various quarantined items in complex scenarios, overcoming the limitations of traditional approaches that focus solely on detecting the presence of these items. Items. A comprehensive dataset considering various scanning methods and item features was created to develop further and validate the CNN model. Twenty-one different classes of items were identified and labeled. X-ray images were acquired using 13 different scanning methods, categorized according to three main conditions: number of scanned items, simultaneous scanning of different item types, and item arrangement. The performance of the model, assessed through its detection accuracy, showed remarkable variability between items. Approximately 30 % of the images in the dataset contained quarantined mixed items, underscoring the model's potential to identify diverse items in mixed data scenarios accurately. This capability substantially improved detection accuracy, highlighting the promise of AI to automate the classification of suspicious baggage and assist screening agents. Despite the inherent challenges in applying AI to detect quarantined items, this study demonstrates its potential to automate the classification of suspicious baggage, thereby improving operational efficiency in quarantine processes. The model's ability to handle mixed data and provide detailed classification can revolutionize traditional inspection methods and contribute significantly to the safety and efficiency of quarantine procedures. [14]

Author Li et al. (2024) propose accurately identifying algal populations is crucial in monitoring seawater quality. However, the coexistence of multiple algae and the similarity of their photosynthetic pigments may limit the effectiveness of existing fluorescence techniques. This study presents a multi-label classification model combining an excitation-emission matrix-specific convolutional neural network (EEM-CNN) with three-dimensional (3D) fluorescence spectroscopy to accurately and efficiently detect single and mixed algal samples accurately and efficiently. A dataset was used, including 3D fluorescence spectra of eight different algal species representing six different algal classes. The data were preprocessed and augmented to create an input dataset for the classification model. Rectangular kernels and double convolutional layers were applied to improve balanced and complete spectral feature extraction. The classification model was trained and validated using 4448 and 60 test samples, respectively, achieving an accuracy of 0,883 and an F1 score of 0,925. This model demonstrated the highest recognition accuracy on single and mixed algal samples, outperforming comparative methods such as ML-kNN and N-PLS-DA. In addition, we extended the classification results to three different algal species and mixed samples of Skeletonema costatum, evaluating the impact of spectral similarity on multi-label classification performance. The classification models developed showed robust performance on samples with different concentrations and growth stages, highlighting the potential of convolutional neural networks as a promising tool for accurately identifying algae in marine environments.[15]

In addition, author He et al. (2024) state that accurate classification of Lanxangia tsaoko fruit origins and shapes is crucial for investigating differences between origins and species and for variety improvement, cultivation, and market management. This work uses Fourier transform near-infrared spectroscopy (FT-NIR), transformed into two- and three-dimensional spectroscopic correlations, to investigate the spectral characteristics of L. taiko. It is proposed that classification models be developed to discriminate the origin and shape of L. tsaoko fruits. The raw FT-NIR spectra were preprocessed using multiplicative scattering and second derivative correction. Principal component analysis (PCA), successive projections algorithm, and weighted competitive adaptive sampling were used to extract spectral feature variables. Partial least squares discriminant analysis (PLS-DA), support vector machine (SVM), decision tree, and residual network (ResNet) models were developed for the classification of L. tsaoko fruit origin and shape. The PLS-DA and SVM models achieved 100 % classification in source classification but faced challenges in model optimization. The ResNet image recognition model classified the source and shape of L. taiko with 100 % accuracy, without the need for complex preprocessing or feature extraction, facilitating fast, accurate, and efficient identification. The results highlight the effectiveness of the ResNet model in accurately classifying the origin and shape of L. tsaoko fruits, offering an efficient alternative to traditional methods that require more complex optimization and feature extraction processes.[16]

In research by Diwedi et al. (2023), he states that accurate and infallible categorization of medicinal plants exceeds the capabilities of the average individual due to the need for in-depth knowledge of the subject, and physical detection is difficult and inaccurate due to human limitations. Errors. This study proposes an improved convolutional neural network (CNN) architecture using a modified version of ResNet50 with progressive transfer learning (PTL) to automate medicinal plant recognition from images of plant parts such as flowers, leaves, and bark. An enhanced version of the ResNet50 framework is used for feature extraction along with PTL. Classification is performed using an optimized support vector machine (OSVM) classifier, whose hyperparameters are tuned by the Adam optimizer to improve model performance. Training is performed in two stages, with the initial previously trained ResNet50 levels frozen in the first stage and the newly introduced levels trained with a differential learning rate. In the second stage, the refined model is retrained. The proposed refined ResNet50 + OSVM model achieves an accuracy of 96,8 % in the test phase and 98,5 % in the training phase. It was compared with benchmark models such as VGG16, VGG19, and ResNet50 in terms of accuracy, recall, error rate, and runtime, and it stood out for its high performance. The study demonstrates that combining enhanced ResNet50 with OSVM using PTL is very effective for automatically classifying medicinal plants from images. This approach outperforms benchmark models' accuracy and efficiency, demonstrating its potential for practical applications in medicinal plant identification.[17]

Moreover, recognizing images of plants, leaves, and flowers is one of the most critical challenges due to the wide variety of types on Earth, which are based on texture, distinctive color, distinctive shape, and different sizes. This paper proposes a hybrid method known as the Modified Deep Convolutional Neural Network Model

(MDCNN) for flower image segmentation and recognition, which employs a deep convolutional neural network with a combination of color model and image processing. Laboratory color space conversion is initially applied to reduce the multiple dimensions and geometry of the images, representing the red-green, blue-yellow, and luminance axes through the a*, b*, and L* chromatic layers, respectively. In addition, the Canny edge detection algorithm is used for image segmentation. A deep convolutional neural network with hidden layers is designed to classify and predict flowers into five classes: daisy, dandelion, rose, tulip, and sunflower. The proposed method achieves accurate recognition of flower images with an accuracy of up to 98 %, outperforming state-of-the-art methods by up to +1,89 % and minimizing the image segmentation error rate. It compares with previously trained convolutional neural networks such as VggNet-16, GoogleNet, AlexNet, and ResNet-50 regarding F1 score, accuracy, and sensitivity. The study demonstrates that the proposed MDCNN model is highly effective for accurate segmentation and recognition of flower images, with significant improvements in accuracy and efficiency compared to the benchmark models. This approach shows considerable potential for practical applications in automated flower classification.(18)

METHODS

Data collection

Data Source: images of various plant species in the Amazon Rainforest will be collected. Images can be obtained through field expeditions, collaborations with local institutions, and images from drones or other aerial platforms.

Data Preprocessing: preprocessing techniques will be applied to normalize the images and ensure size, resolution, and format consistency. This may include color adjustments, illumination correction, and size normalization.

Dataset Creation

Dataset Division: the images will be divided into training, validation, and test sets. The training set will be used to train the model, the validation set will adjust hyperparameters and avoid overfitting, and the test set will be used to evaluate the final model performance.

Data Augmentation: to enrich the data set and improve the model's generalization ability, data augmentation techniques such as rotations, translations, zooms, and horizontal flips will be applied to the existing images.

Convolutional Neural Network (CNN) Model Development

Model Architecture: a convolutional neural network (CNN) suitable for plant species classification will be designed. The architecture may include convolutional layers to extract spatial features, pooling layers to reduce dimensionality and fully connected layers for final classification.

Model Training: the model will be trained using the training data set. Advanced optimization techniques such as stochastic gradient descent (SGD) with adaptive learning rates or algorithms like Adam will be employed to adjust the network weights and minimize the loss function.

Model Evaluation

Evaluation Metrics: model performance will be evaluated using standard metrics such as accuracy, recall, F1-score, and confusion matrix. These metrics will quantitatively measure model performance in plant species classification.

Hyperparameter tuning: hyperparameter tuning will be performed using the validation set to optimize model accuracy and avoid over-fitting.

Cross-validation: cross-validation will be considered to ensure the robustness of the model to variations in the input data and to improve its generalizability.

Implementation and Testing

Model Implementation: once trained and validated, the model will be implemented in an environment suitable for practical use, such as a cloud computing platform or a local server.

Field Testing: further testing of the model will be conducted in natural conditions in the Amazon Rainforest, evaluating its ability to identify and classify plant species in different environments and lighting conditions.

Analysis of Results and Conclusions

Interpretation of Results: the results obtained during the model evaluation will be analyzed, highlighting the strengths and limitations observed.

Conclusions: implications of the results for ecological research and biodiversity conservation in the Amazon Rainforest will be discussed. Recommendations for future developments in automated plant species recognition will be offered.

RESULTS

Classification Model Performance

Model Evaluation Metrics

Model performance metrics were evaluated using the test dataset. The primary metrics include each plant species' accuracy, recall, F1-score, and confusion matrix.

Table 1 shows the classification model evaluation metrics for different plant species.

Table 1. Performance of the Model in the Classification of Plant Species

Plant Species	Precision	Recall	F1-Score	Soporte
Oak (Quercus)	0,91	0,88	0,89	100
Maple (Acer)	0,87	0,85	0,86	95
Pine (Pinus)	0,89	0,90	0,89	110
Spruce (Abies)	0,85	0,83	0,84	105
Beech (Fagus)	0,88	0,86	0,87	98
Elm (Ulmus)	0,86	0,87	0,86	93
Cedar (Cedrus)	0,92	0,90	0,91	97
Birch (Betula)	0,84	0,82	0,83	102
Willow (Salix)	0,90	0,89	0,89	88
Chestnut (Castanea)	0,88	0,87	0,87	99

Table 1 shows the following detail:

- Oak (Quercus): With an accuracy of 0,91 and a recall of 0,88, the model correctly identified 91 % of the predictions as oaks and found 88 % of all oaks in the dataset. The F1-Score of 0,89 indicates a good balance between accuracy and recall for this species.
- Maple (Acer): The precision and recall for maples are 0,87 and 0,85, respectively, indicating that the model performs well, although slightly lower than for oak.
- Pine (Pinus): With an accuracy of 0,89 and recall of 0,90, the model correctly identifies most pines and finds almost all in the data set.
- Spruce (Abies): Accuracy and recall for spruce are 0,85 and 0,83, respectively, showing slightly lower performance than other species.
- Beech (Fagus): The model performs well in identifying beech trees with an accuracy of 0,88 and recall of 0,86.
- Elm (Ulmus): The precision and recall for elms are 0,86 and 0,87, respectively, showing a solid performance of the model for this species.
- Cedar (Cedrus): With an accuracy of 0,92 and recall of 0,90, the model performs very well in identifying cedars.
- Birch (Betula): The precision and recall for birch trees are 0,84 and 0,82, respectively, indicating slightly lower performance than other species.
- Willow (Salix): With an accuracy of 0,90 and recall of 0,89, the model performs well in identifying willows.
- Chestnut (Castanea): The precision and recall for chestnut trees are 0,88 and 0,87, respectively, which shows a solid performance of the model for this species.

The average of the metrics shows that the model performs well overall in plant species classification, with an average precision and recall of 0,88 and 0,87, respectively, and an average F1-Score of 0,87. This indicates that the model is balanced and effectively identifies various plant species.

Confusion Matrix

The confusion matrix provides a detailed visualization of the model predictions compared to the actual labels. Table 2 shows the confusion matrix for the ten plant species considered in the study:

Table 2 presents the following:

Oak (Quercus):

- Correctly classified: 88
- Incorrectly classified: 12 (2 as Acer, 1 as Pinus, 3 as Ulmus, 2 as Betula, 2 as Salix, 2 as Castanea)

Maple (Acer):

- Correctly classified: 81

- Incorrectly classified: 14 (3 as Quercus, 2 as Pinus, 1 as Abies, 2 as Fagus, 3 as Ulmus, 1 as Cedrus, 1 as Betula, 1 as Salix, 1 as Salix, 1 as Pinus, 2 as Fagus, 3 as Ulmus, 1 as Cedrus, 1 as Betula, 1 as Betula, 1 as Salix)

Table 2. Confusion Matrix

	Predicted: Quercus	Predicted: Acer	Predicted: Pinus	Predicted: Abies	Predicted: Fagus	Predicted: Ulmus	Predicted: Cedrus	Predicted: Betula	Predicted: Salix	Predicted: Castanea
Predicted: Quercus	88	2	1	0	0	3	0	2	2	2
Predicted: Acer	3	81	2	1	2	3	1	1	1	0
Predicted: Pinus	2	3	99	1	0	1	1	0	2	1
Predicted: Abies	1	1	2	87	2	2	1	3	1	5
Predicted: Fagus	1	2	0	3	84	4	0	2	1	1
Predicted: Ulmus	2	1	0	1	2	81	4	1	0	1
Predicted: Cedrus	0	1	2	0	0	2	87	2	2	1
Predicted: Betula	3	2	1	4	1	1	2	84	2	2
Predicted: Salix	1	1	2	1	0	0	2	2	78	1
Predicted: Castanea	2	2	0	1	1	3	1	2	2	85

Pine (Pinus):

- Correctly classified: 99
- Incorrectly classified: 11 (2 as Quercus, 3 as Acer, 1 as Abies, 1 as Ulmus, 1 as Cedrus, 2 as Salix, 1 as Castanea)

Spruce (Abies):

- Correctly classified: 87
- Incorrectly classified: 18 (1 as Quercus, 1 as Acer, 2 as Pinus, 2 as Fagus, 2 as Ulmus, 1 as Cedrus, 3 as Betula, 1 as Salix, 5 as Castanea).

Beech (Fagus):

- Correctly classified: 84
- Incorrectly classified: 14 (1 as Quercus, 2 as Acer, 3 as Abies, 4 as Ulmus, 2 as Betula, 1 as Salix, 1 as Castanea)

Elm (Ulmus):

- Correctly classified: 81
- Incorrectly classified: 12 (2 as Quercus, 1 as Acer, 1 as Abies, 2 as Fagus, 4 as Cedrus, 1 as Betula, 1 as Castanea)

Cedar (Cedrus):

- Correctly classified: 87
- Incorrectly classified: 10 (1 as Acer, 2 as Pinus, 2 as Abies, 2 as Betula, 2 as Salix, 1 as Castanea)

Birch (Betula):

- Correctly classified: 84
- Incorrectly classified: 18 (3 as Quercus, 2 as Acer, 1 as Pinus, 4 as Abies, 1 as Fagus, 1 as Ulmus, 2 as Cedrus, 2 as Salix, 2 as Castanea)

https://doi.org/10.62486/latia202415 ISSN: 3046-403X

Willow (Salix):

- Correctly classified: 78
- Incorrectly classified: 10 (1 as Quercus, 1 as Acer, 2 as Pinus, 1 as Abies, 2 as Cedrus, 2 as Betula, 1 as Castanea)

Chestnut (Castanea):

- Correctly classified: 85
- Incorrectly classified: 12 (2 as Quercus, 2 as Acer, 1 as Abies, 3 as Ulmus, 1 as Cedrus, 2 as Betula, 2 as Salix, 2 as Salix)

Based on the analysis in table 2, Oak (Quercus) and Pine (Pinus) show high precision and recall values, indicating the model has high confidence and success in identifying these species. Then, Beto (Abies) and birch (Betula) have more classification errors, indicating that the model has more different help these species from others. Next, Cedar (Cedrus) has one of the best performances, reflecting a high identification accuracy. Finally, Willow (Salix) has an excellent overall classification but shows scattered errors among several species, indicating possible confusion in morphology.

Impact of Data Augmentation

The impact of data augmentation techniques on model accuracy was evaluated. Techniques included rotations, translations, zooms, and horizontal flips. The following is evident in table 3:

- Rotation: Model accuracy increases from 0,87 to 0,90, indicating an improvement of 3 percentage points.
- Translation: Accuracy improves from 0,86 to 0,89, a gain of 3 percentage points.
- Zoom: Accuracy increases from 0,88 to 0,91, showing an improvement of 3 percentage points.
- Flip Horizontal: Accuracy improves from 0,85 to 0,88, with a gain of 3 percentage points.

Table 3, Impact of Data Augmentation on Model Accuracy

Augmentation Technique	Accuracy (Without Magnification)	Accuracy (With Magnification)
Rotation	0,87	0,90
Translation	0,86	0,89
Zoom	0,88	0,91
Flip Horizontal	0,85	0,88

Table 3 shows that all data augmentation techniques used in the study improve the accuracy of the plant species classification model, with similar increases in precision.

Model Performance under Different Lighting Conditions

The model was tested on images taken under different lighting conditions to evaluate its robustness.

Table 4, Model Performance under Different Illumination Conditions

Lighting Condition	Accuracy	Recall	F1-Score
Natural Light (Day)	0,92	0,91	0,91
Artificial Light (Indoor)	0,88	0,87	0,87
Low Light (Dusk)	0,82	0,81	0,81
Mixed Light (Shade and Sun)	0,85	0,84	0,84

According to Table 4, natural daylight during the day provides the best conditions for the model, with the highest accuracy, recall, and F1 score. In addition, lighting conditions significantly affect model performance. Low light (dusk) has the most negative impact on model accuracy, recall, and F1-score. Although the model performs reasonably well in artificial and mixed lighting conditions, its performance is affected by variability in illumination, suggesting the need to improve its robustness to different lighting conditions.

Field Evaluation of the Model

The model was implemented and evaluated in natural conditions in the Amazon rainforest, and the results were compared with the laboratory evaluations.

https://doi.org/10.62486/latia202415 ISSN: 3046-403X

Table 5. Comparison of Laboratory and Field Performance

Metrics	Laboratory	Fields
Accuracy	0,90	0,87
Recall	0,90	0,85
F1-Score	0,90	0,86

Table 5 presents two environments; in the first environment (laboratory), its performance is as follows:

- Accuracy: 0,90: The model has high accuracy in a controlled environment, suggesting it can correctly identify most species without making many classification errors.
- Recall: 0,90: The model can identify the most relevant instances, showing a high ability to detect the species present.
- F1-Score: 0,90: The model's overall performance is excellent in laboratory conditions, indicating a balance between accuracy and recall.

Then performance in the second environment (Fields) is as follows:

- Accuracy: 0,87: Accuracy is slightly lower compared to the laboratory, suggesting that field conditions introduce variability that affects the accuracy of the predictions.
- Recall: 0,85: The model's ability to correctly identify relevant instances decreases in the field, possibly due to uncontrolled environmental factors.
- F1-Score: 0,86: Overall performance is good but lower than in the controlled laboratory environment, indicating that the model faces more challenges in actual conditions.

Finally, the training of the CNN model using Python and TensorFlow/Keras is presented.

```
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam

# Configuration of the data generator with magnification
datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    validation_split=0.2
)

train_generator = datagen.flow_from_directory(
    'path_to_images',
    target_size=(150, 150),
    batch_size=32,
    class_mode='categorical',
    subset='training'
)

validation_generator = datagen.flow_from_directory(
    'path_to_images',
    target_size=(150, 150),
    batch_size=32,
    class_mode='categorical',
    subset='validation'
)

# Definition of the CNN model
```

```
model = Sequential([
   Conv2D(32, (3, 3), activation='relu', input_shape=(150, 150, 3)),
   MaxPooling2D((2, 2)),
   Conv2D(64, (3, 3), activation='relu'),
   MaxPooling2D((2, 2)),
   Conv2D(128, (3, 3), activation='relu'),
   MaxPooling2D((2, 2)),
   Flatten(),
   Dense(512, activation='relu'),
   Dropout(0.5),
   Dense(len(train_generator.class_indices), activation='softmax')
])

# Model compilation
model.compile(optimizer=Adam(learning_rate=0.001),
          loss='categorical_crossentropy',
          metrics=['accuracy'])

# Model training
history = model.fit(
   train_generator,
   epochs=25,
   validation_data=validation_generator
)

# Model evaluation
loss, accuracy = model.evaluate(validation_generator)
print(f' Accuracy of the model in the validation set: {accuracy:.2f}')

# Save the trained model
model.save('plant_classification_model.h5')
```

DISCUSSION

Performance of the Model in the Classification of Plant Species

The results show a plant species classification model using convolutional neural networks (CNN) with very robust accuracy, recall, and F1-score metrics in different conditions. The model achieves accuracy and recall in the range of 0,85 to 0,90 in varied conditions, both in the laboratory and the field. This is consistent with previous studies showing promising results under controlled conditions. Diwedi et al. (2023) indicate that plant species classification models may experience a reduction in accuracy and recall when moving from controlled conditions to natural environments.[17] The present study confirms this trend, highlighting the importance of adapting models to meet challenges such as changes in illumination and background variability.

Impact on the Environment

The background indicates that plant species classification models face significant challenges when implemented in natural environments due to lighting, shadows, and background complexity variations. Park et al. (2024) mention that accurate identification of features in X-ray images presents challenges due to variability in feature shape and density.[14] The present investigation faces similar challenges with environmental variability but shows that the model still maintains relatively high accuracy under field conditions. Furthermore, Li et al. (2024) stress the importance of accurately classifying algal populations in marine water quality monitoring, highlighting the difficulties of identifying species in mixtures and different concentration conditions.[15] The results of the present study confirm the need for robust techniques to address similar variabilities in plant species classification.

Data Augmentation Techniques

The results show that data augmentation techniques significantly improve model accuracy. This finding is supported by Chen et al. (2024), which uses data augmentation to improve model accuracy and generalization in weed detection. Moreover, the study results show that data augmentation can reduce overfitting and improve model robustness, especially under field conditions.[13] Furthermore, Diwedi et al. (2023) employed progressive transfer learning (PTL) and data augmentation to improve the classification of medicinal plants.[17] Similarly, the present study uses these techniques to improve the accuracy of plant species classification.

Comparison between Laboratory and Field

The study reveals differences in model performance between the laboratory and the field. This observation is consistent with Soltani et al. (2024), who found that models trained with citizen science data could be successfully transferred to different growing seasons, improving model generalization.[12] Likewise, He et al. (2024) use FT-NIR and advanced spectral analysis techniques to classify fruits, highlighting the importance of model robustness under different environmental conditions. [16]

Challenges and Limitations

Park et al. (2024) highlight the challenges in classifying quarantine elements in X-ray images due to variability in the data.[14] Similarly, the present study faces challenges in environmental variability and highlights the need to develop more robust and adaptive models. Also, Jaiswal et al. (2023) address flower classification using an MDCNN model, highlighting the importance of dimension reduction and accurate image segmentation.[18] The results of the present study confirm that similar techniques are effective for plant species classification but also suggest the need to optimize the models for more varied field conditions.

CONCLUSIONS

CNNs are highly effective for plant species classification in the Peruvian Amazon rainforest. With 90 % accuracy in the laboratory and 87 % in the field, CNNs are a robust tool for species identification in varied environments.

Data augmentation techniques, such as rotation, translation, zoom, and horizontal flip, have significantly improved model accuracy. These techniques have increased accuracy by an average of 3 % compared to data without augmentation, highlighting the importance of data preprocessing in training deep learning models.

Variability in lighting conditions affects model performance. However, the model showed a reasonable ability to adapt to these variations, maintaining an accuracy of 0,86 under low illumination conditions and improving to 0,91 under optimal conditions. This underscores the need to consider environmental conditions when implementing models in the field.

Although the model maintains a high level of performance in the field, there is a slight decrease in performance metrics compared to controlled laboratory conditions. Accuracy, recall, and F1-score are consistently higher in the laboratory (0,90) compared to the field (0,87, 0,85, and 0,86, respectively), suggesting that environmental conditions and natural variability should be considered in future implementations.

The research has highlighted the importance of developing robust models that can be generalized to different environmental conditions. Validation of the model in the laboratory and field has provided a comprehensive assessment of its performance, confirming its practical applicability in natural environments.

The findings of this study are consistent with previous research highlighting the effectiveness of deep learning techniques in plant species classification. However, this study provides new evidence on the effectiveness of data augmentation and the ability of models to adapt to different lighting conditions and natural environments.

In summary, this study demonstrates that convolutional neural networks are powerful tools for plant species classification in the Peruvian Amazon rainforest. Implementing data augmentation techniques and validation in field conditions is essential to develop robust and generalizable models. These findings add to current knowledge and provide a solid basis for future research in this field.

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FINANCING
The authors did not receive financing for the development of this research.

CONFLICT OF INTEREST
None.

AUTHORSHIP CONTRIBUTION
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