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Deep Learning Application for Biodiversity Conservation and Educational Tourism in Natural Reserves

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Abstract: Natural reserves, such as the Santurbán Moor in Colombia, are ecologically important but face significant threats from activities like mining and agriculture. Preserving biodiversity in these ecosystems is essential for maintaining ecological balance and promoting sustainable tourism practices. Identifying plant species in these reserves accurately is challenging due to environmental variability and species similarities, complicating conservation efforts and educational tourism promotion. This study aims to create and assess a mobile application based on deep learning, called FloraBan, to autonomously identify plant species in natural reserves, enhancing biodiversity conservation and encouraging sustainable and educational tourism practices. The application employs the EfficientNet Lite4 model, trained on a comprehensive dataset of plant images taken in various field conditions. Designed to work offline, the application is particularly useful in remote areas. The model evaluation revealed an accuracy exceeding 90% in classifying plant images. FloraBan was effective under various lighting conditions and complex backgrounds, offering detailed information about each species, including scientific name, family, and conservation status. The ability to function without internet connectivity is a significant benefit, especially in isolated regions like natural reserves. FloraBan represents a notable improvement in the field of automated plant identification, supporting botanical research and efforts to preserve biodiversity in the Santurbán Moor. Additionally, it encourages educational and responsible tourism practices, which align with sustainability goals, providing a useful tool for both tourists and conservationists.

Keywords: deep learning; biodiversity conservation; plant identification; sustainable tourism; mobile applications; natural reserves

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1. Introduction

The Santurbán paramo, recognized for its unique biome and its strategic and ecological significance, faces considerable environmental challenges due to mining and agricultural activities, as well as increased tourism. These challenges highlight the need to develop preservation strategies that balance economic use with ecological conservation, integrating sustainable tourism practices that promote the socioeconomic development of local communities [1,2]. Illegal mining in this area has had severe effects, particularly evidenced by the elevated levels of mercury in the Suratá River, the main water source for the metropolitan area of Bucaramanga, a city located in northeastern Colombia, known for its economic importance and capital of the department of Santander. Since mid-2022, mercury concentrations have been recorded at levels exceeding the permitted limit by eighty-one times, posing a public health risk [3]. The extraction of gold and silver, mostly conducted by artisanal miners without proper permits, has intensified the environmental degradation of the region. The absence of sustainable management systems and the prevailing informality in the artisanal and small-scale mining sector have exacerbated the economic, social, and environmental issues in the region [4]. It is essential to develop and implement comprehensive management systems that promote economic, social, and ecological sustainability in these extractive activities to mitigate their negative impact. The preservation of Santurbán′s unique biodiversity is crucial not only for maintaining ecological balance but also as a valuable tourist attraction [5,6]. The biological richness of the paramo, essential for water resource generation, requires effective long-term conservation strategies, encouraging both tourists and residents to commit to protecting these resources [7]. The Colombian government has recognized the importance of the paramo and, as a result, has regulated land use by creating a protected area that must remain free from any polluting activities [8,9]. This measure has led to the repurposing of lands previously intended for mining or agriculture, thereby limiting the economic alternatives available to the community. Consequently, local communities have organized to develop nature tourism as a new economic option [10]. The location of the Santurbán paramo within Colombia is illustrated in Figure 1.

Figure 1. Location of Santurbán moor in Colombia, reference image.

This study proposes the creation of a mobile application designed to promote conscious and responsible tourism in Santurbán, in response to the significant growth of the tourism sector in Santander, Colombia. This tourism boom has become a vital source of income and employment for the region [11]. Despite the restrictions imposed by the Colombian government on potentially harmful activities in this fragile ecosystem, such as mining, the community has successfully redirected its economy toward tourism. Therefore, sustainable practices that encompass hospitality, gastronomy, and outdoor activities are necessary, without compromising the environmental integrity of the paramo [12,13].

In this context, the incorporation of advanced technologies in tourism applications has opened a range of possibilities for biodiversity conservation in the paramo of Santurbán. These technologies enable precise monitoring, and species identification has extended beyond scientific research, allowing for the implementation of effective conservation strategies on the ground. Biodiversity conservation in the paramo of Santurbán is linked to the understanding and management of the physical landscape, as this provides the necessary conditions for the region's ecological health. As Qian et al. [14] indicate, landscape connectivity and structure are fundamental to maintaining biodiversity, especially in sensitive ecosystems such as paramos, which are vulnerable to environmental changes and human activities [15,16].

Accurate monitoring and species identification are fundamental pillars in the conservation of biodiversity in Santurbán. These technologies enable efficient and precise data collection, as well as real-time analysis that can support timely conservation decision-making. Technological applications, such as those developed in the AdVENt project, allow for the rapid and accurate identification of flora and fauna species through images, leveraging the power of artificial intelligence (AI) [17,18]. Additionally, the Internet of Things (IoT) facilitates the deployment of sensors and monitoring devices in natural areas, enabling real-time data collection on various environmental parameters [19,20], which is crucial for detecting changes in ecosystems, identifying threats to biodiversity, and assessing the effectiveness of implemented conservation measures.

Preserving the physical landscape in Santurbán not only protects local biodiversity but also ensures the continuity of vital ecosystem services, such as water regulation, which is crucial for both human communities and ecological balance. Furthermore, the conservation of landscapes and biodiversity directly benefits the region's socioeconomic development. The transition to a sustainable tourism model, based on the natural wealth of the paramo, provides communities with a viable economic alternative in a context where other activities, such as mining, have been restricted. As Brauman et al. [21] note, well-preserved landscapes are not only more resilient but can also attract investments in ecotourism, improving residents' quality of life and promoting balanced development.

Proper management of the physical landscape in Santurbán is essential both for biodiversity and for regional development, which harmonizes environmental protection with economic progress. Land use regulation and the creation of protected areas, as suggested by Zhao et al. [22] in relation to biodiversity preservation and the promotion of socioeconomic benefits, can serve as a model for Santurbán, where biodiversity conservation and socioeconomic development are closely intertwined.

Technology is a key ally in conservation, with Industry 4.0 innovations such as artificial intelligence, cloud computing, and big data analytics transforming methodologies in tourism and conservation [23,24]. These technologies enable efficient biodiversity management through precise species identification and environmental impact monitoring, enhancing the tourist experience and promoting sustainable practices [25,26]. Recent research highlights the potential of artificial intelligence and machine learning to innovate in ecosystem conservation and combat deforestation [27]. When applied through mobile applications, these technologies offer novel solutions for ecosystem monitoring, real-time species recognition, and fostering a deeper understanding of biodiversity [28,29]. An example of this is the FloraBan mobile application, designed to identify endemic plant species in the paramo of Santurbán, which has demonstrated high accuracy in image classification, even in remote areas without internet connectivity. This technology not only facilitates scientific research but also ensures that both tourists and residents actively contribute to the protection of this valuable ecosystem [17].

The results of this study contribute to science and practice in several meaningful ways:

- **Implementation of the EfficientNet Lite4 Model:** The integration of this model into the FloraBan mobile application facilitates the efficient identification of endemic plant species under challenging imaging conditions. This demonstrates the capability of the EfficientNet Lite4 model to adapt and function amid environmental factors that complicate visual recognition, such as variable lighting and similar backgrounds.
- **Accuracy in Plant Image Classification:** The application has demonstrated an accuracy rate exceeding 90% in classifying images of endemic plants in Santurbán. This accuracy

is essential for reliable species identification and provides a robust tool for botanical research and environmental monitoring.

- **Autonomous Functionality Without Internet Dependence:** The application's ability to operate autonomously, without requiring an Internet connection, is particularly relevant for use in remote areas. The tool can be utilized in locations with limited connectivity, such as the paramo of Santurbán, increasing its utility for field researchers and local communities.
- **Contribution to Biodiversity Conservation and Advances in Botany:** By applying emerging technologies, the study not only advances botanical science but also contributes to biodiversity conservation. The FloraBan application provides a useful tool to promote more conscious and educational tourism in the Santurbán paramo ecosystem, encouraging tourists and residents to recognize and value plant diversity, which in turn fosters greater understanding and conservation of the region's natural resources.

2. Methodology

2.1. Study Site and Data Collection

This study focused on the most frequented tourist areas within the Paramo de Santurbán, Colombia, aiming to represent the flora most likely encountered by visitors. The primary sampling location was Las Lagunas Negras (7.2809° N, −72.8867° W), with additional visits to Laguna Pajarito situated between the municipalities of Vetas and Corregimiento de Berlin (Tona) in the Santander Department. The sampling altitudinal range spanned from 3200 to 3800 m above sea level.

Data collection involved seven field visits over four months. Plant species diversity was documented under varying illumination, climate, and phenological stages (e.g., flowering, fruiting). This approach facilitated a comprehensive understanding of the environment and the studied species [30].

Image capture was conducted using a smartphone with a vertically mounted dual camera system. The primary camera possessed a 48-megapixel sensor, f/1.8 aperture, phase detection autofocuses (PDAF), and electronic image stabilization (EIS). Video recording capabilities included resolutions up to 2160p at 30 fps and 1080p at various speeds (30, 60, and 120 fps), enabling detailed visual documentation.

A total of 1200 images were collected, encompassing 12 identified plant species, with 100 images per species selected for training and validating the identification model. These species are further detailed in Figure 2 and Table 1.

Table 1. Descriptions of plants identified in the dataset.

Identification	Scientific Name	Description	Image
1	*Espeletia boyacensis Cuatrec* [31]	A medium-sized frailejón, reaching heights of up to 60 cm. The leaves are leathery and succulent, with an oblanceolate blade measuring up to 45 cm in length, tapering at the base into a pseudo-petiole of 2 to 8 cm. They possess an acute apex, entire margins, and a prominent midrib on the abaxial surface. The inflorescence is axillary, oval, and hyaline, with flowers ranging from yellow to brown, and features pedicellate glands.	

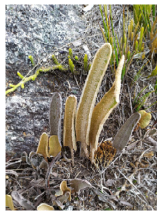
Table 1. *Cont.*

Identification	Scientific Name	Description	Image
2	*Espeletia conglomerata A.C.Sm* [31]	A medium-sized frailejón, reaching up to 2 m in height, characterized by a stem-like extension and a rosette approximately 50 cm in diameter. The rosette consists of broad leaves displaying green and yellow hues. It produces floral stems with yellow blooms that emerge from the center of the rosette. This species is native to Colombia, where it is found primarily in the departments of Boyacá, Santander, and Norte de Santander.	
3	*Senecio niveoaureus Cuatrec* [32,33]	This species belongs to the Asteraceae family and is similar to Frailejones. It is primarily cultivated as an ornamental plant in mountainous regions. It forms clusters of rosettes composed of soft, densely pubescent, silvery-white leaves that resemble "rabbit ears". The inflorescences are yellow, with small, delicate petals.	
4	*Arcytophyllum thymifo-lium (Ruiz & Pav.) Standl* [34]	A pulvinate shrub with opposite, sessile, coriaceous, oblong-linear leaves, featuring sheathing stipules. The flowers are solitary, axillary, hermaphroditic, actinomorphic, tetramerous, and epigynous. The hypanthium is ovoid, and the calyx is lobed with persistent intercalycular teeth. The corolla is hypocrateriform and white. The androecium consists of epipetalous stamens inserted into the corolla tube. The gynoecium contains a bilocular ovary and a bifid stigma. The fruit is a septicidal capsule, crowned by sepals and intercalycular teeth.	
5	*Monticalia vernicosa (Sch.Bip. ex Wedd.) C.Jeffrey* [35]	Woody plant in the form of a shrub, with slender leaves that resemble those of the plant commonly known as rosemary. It is a medium-sized shrub, not exceeding two meters in height, with a woody and dark-colored trunk. The leaves are alternate, ovate to oblong, with entire or finely denticulate margins, and have a pronounced petiole, very similar to those of the culinary rosemary. The inflorescences are yellow in color.	
6	*Acaena cylindristachya Ruiz & Pav* [36]	A rosette-forming herb with a white indumentum and small, inconspicuous flowers. This species tends to form dense, low-growing mats that can spread extensively, often creating a thick vegetative carpet. Its leaves are compound, composed of small, toothed leaflets, dark green in color, and arranged alternately along the stem. Although the flowers are diminutive, they are not particularly conspicuous.	

Table 1. *Cont.*

Identification	Scientific Name	Description	Image
7	*Puya asplundii L.B.Sm* [37]	Puya is a perennial plant belonging to the Bromeliaceae family, with a rosette structure similar to that of aloe or pineapple. These are perennial herbs, acaulescent or with short stems, of medium stature (0.7 m), growing either solitarily or in clumps. Their leaves are arranged in rosettes and sheathed, with triangular or nearly triangular leaf blades and serrated margins. The inflorescence is scapose, simple or branched twice, with flowers arranged either loosely or densely. The flowers are perfect, pedicellate, trimerous, and hypogynous; they have 3 free sepals, shorter than the petals, tomentose to glabrescent, ranging from green to brown, and 3 spatulate petals, free, with an obtuse to rounded apex, pale yellow in color.	
8	*Hypericum juniperinum (L.fil.) Kunth* [38]	Small shrub with striking yellow flowers and a complex morphological variation in size, growing in high mountain areas. This terrestrial shrub reaches a height of 0.2 m, with erect to decumbent stems, initially quadrangular and later becoming rounded, exfoliating irregularly. Its leaves are simple, opposite, and decussate, with leaf blades measuring 6–14 × 1.5 mm, slightly imbricate at the base and with an acute apex. The flowers are yellow, solitary, and terminal, positioned on short axes.	
9	*Alchemilla alpina* L. [31]	Perennial herbaceous plant belonging to the Rosaceae family. This species has a rhizomatous base and arching stems measuring 10 to 20 cm in height. Its leaves are divided into 5 to 7 lanceolate leaflets, 2 to 3.5 cm in length, green and glabrous on the upper surface, and silvery and finely pubescent on the underside. The leaflets have small-toothed apices and long petioles. The flowers are medium-sized, about 20 mm in diameter, yellow in color, and arranged in dense glomerules.	
10	*Disterigma empetrifo-lium (Kunth) Nied. ex Drude* [39]	Dwarf, creeping shrub, often prostrate and rhizomatous, forming cushions only a few centimeters high. The stems are terete and dark brown, while the branches are subterete, angular, striated, and densely puberulent with white hairs. The rhizomes bear bracts resembling miniature leaves. The leaves are whorled, simple, congested, and imbricated, with subterete petioles measuring 0.5 to 1.5 mm in length, and canaliculated. The inflorescence is axillary and pink, with up to 6 bisexual flowers. The fruits are spherical, violet-colored berries.	

Table 1. *Cont.*

Identification	Scientific Name	Description	Image
11	*Lycopodium clavatum* L. [40]	It is a toxic, creeping plant with numerous branches that can reach up to 20 cm in length. It belongs to the broad genus of lycopods, commonly known as ground pines, from the family Lycopodiaceae. These are non-flowering, vascular plants that can be terrestrial or epiphytic, characterized by their abundant branching. They can be erect, prostrate, or creeping, with tiny, simple, scaly, or spiky leaves that densely cover the stems and branches.	
12	*Elaphoglossum engelii (H.Karst.) Christ* [41]	It belongs to the fern genus within the Dryopteridaceae family. It is primarily epiphytic, though it is rarely found in a terrestrial form. The rhizome measures up to 12 mm in diameter, being shortly creeping or erect. The leaves, which range from 8 to 30 cm in length, are closely arranged. The petiole scales, 6 mm wide, are ovate to lanceolate, spreading, pale orange in color, and with eroded margins. The leaf blade measures between 6 and 20 cm in length and 2 to 5 cm in width, and is narrowly elliptical to lanceolate-ovate, with a subcoriaceous texture. The base is broadly cuneate to rounded, and the apex is obtuse.	

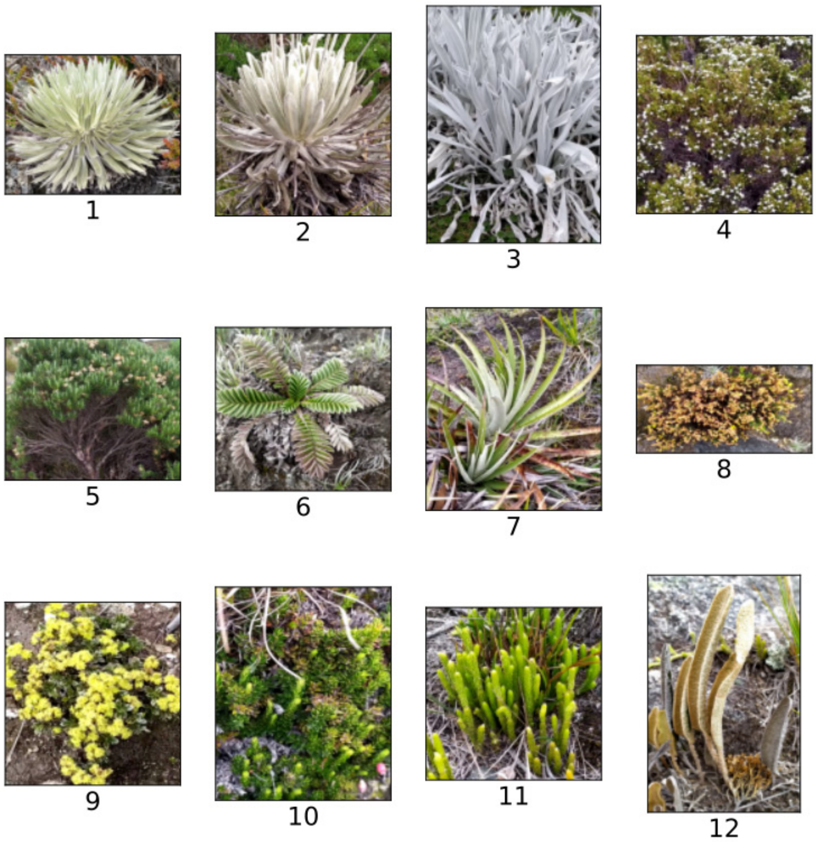


Figure 2. Diversity of selected plant species in the Santurbán paramo.

2.2. Data Generation and Image Preprocessing

Python tools, including OpenCV libraries, were employed for data generation and pre-processing to facilitate the automatic image classification of endemic plant species from the Paramo de Santurbán. The process was designed to adapt the images to the specifications required by the machine learning system, following a methodology that covered stages from initial data collection to preparation for analysis [26,42].

During field visits, videos of each plant species were recorded to simulate a tourist's perspective at varying angles (frontal, upper, lateral) and distances. Representative frames were then extracted from these videos. A Python script developed using the OpenCV library, processed the videos, determining the total frame count and implementing a uniform image extraction protocol. The algorithm analyzed each frame, ensuring it met the pre-established quality and relevance criteria before resizing and storing them in a numbered sequence, ultimately generating 100 frames per species. This automated process optimized resource usage and eliminated the need for manual intervention, which is critical for efficiently managing large datasets.

Following video processing, the dataset for training the classification model was created. A Python script called "image trimmer", also developed with OpenCV, was employed to manually crop images. This script automatically configured paths and directories, verified or created the label folder, and provided an interactive interface for selecting regions of interest with a mouse, subsequently storing the cropped sections. This approach ensured high accuracy in selecting the relevant plant areas for classification, resulting in a high-quality dataset suitable for automatic classification tasks.

The integration of these scripts enabled a seamless transition from video capture to dataset generation, reducing the possibility of human error and enhancing the reproducibility of the process.

2.3. *EfficientNet Architecture*

EfficientNet, a family of convolutional neural networks developed by Google AI [43], is recognized for its notable efficiency and accuracy. Its design utilizes a compound scaling method that balances network depth, width, and resolution adjustments through a compound coefficient, optimizing both accuracy and efficiency. This approach contrasts with previous methods that scaled these dimensions independently [43].

The base EfficientNet architecture is systematically scaled to create models ranging from EfficientNet-B0 to EfficientNet-B7, with increasing size and theoretical accuracy. This system enables network adaptation to various resource constraints, as demonstrated in recent research [44,45].

Despite their smaller size, EfficientNet models achieve comparable or superior accuracy compared to larger models. For instance, EfficientNet-B7 attains 84.3% top-1 accuracy on ImageNet with only 66 million parameters, whereas GPipe requires 556 million parameters to achieve the same accuracy [43]. This size efficiency without compromising accuracy represents a significant advancement in convolutional neural networks.

Table 2 presents a comparison of accuracy and size (parameter count) for several models, highlighting the efficiency of the EfficientNet models [43].

Table 2. Comparison of efficiency and accuracy in neural network models.

Model	Top-1 Accuracy on ImageNet (%)	Number of Parameters (Millions)
ResNet-152	77.8	60
EfficientNet-B1	79.1	7.8
ResNeXt-101	80.9	84
EfficientNet-B3	81.6	12
SENet	82.7	146
NASNet-A	82.7	89
EfficientNet-B4	82.9	19
GPipe	84.3	556
EfficientNet-B7	84.3	66

Table 2 demonstrates the high accuracy of EfficientNet models with a reduced number of parameters compared to other reference models, highlighting their resource efficiency. This characteristic was crucial for selecting the EfficientNet-Lite model in this project due to the need to balance accuracy and performance on mobile devices for research purposes.

EfficientNet Lite4 is a variant specifically designed for resource-constrained devices such as mobile phones. By excluding the more complex Squeeze-and-Excitation (SE) blocks and utilizing ReLU (Rectified Linear Unit) activations instead of Swish, this architecture is simplified, reducing the computational load and enabling faster inference. This balance between accuracy and efficiency makes it suitable for real-time applications on mobile devices, as discussed by [46].

EfficientNet Lite4 has been applied across various domains, including gesture recognition systems for mobile interfaces, disease identification in crops, and automated weed classification in crop fields. These applications illustrate its capability to handle complex computer vision tasks within the limitations of mobile devices. Specific examples of how EfficientNet Lite4 has improved accuracy in agricultural diagnostics and automated weed detection are detailed in [47,48].

2.4. Implementation in a Mobile Application for Plant Species Identification

This study presents the development of a mobile application for identifying plant species in the Paramo de Santurbán. The application utilizes a convolutional neural network (CNN) approach with the EfficientNet-Lite model, leveraging its aforementioned advantages, and integrates TensorFlow Lite. This resulted in a Flutter application for Android devices intended for practical field implementation.

2.4.1. Model Configuration and Training

The plant image classification model employed the EfficientNet Lite4 architecture, chosen for its balance of accuracy and performance on resource-constrained mobile devices. Implementation utilized TensorFlow Lite, enabling efficient execution of deep learning models on mobile platforms.

Model training was conducted using TensorFlow Lite Model Maker [49], simplifying model setup and training within TensorFlow. The dataset was divided into training (90%), validation (5%), and test (5%) sets using the data_split function. A batch size of 9 images was chosen to balance computational load and memory, and training was performed for 10 epochs to prevent overfitting while ensuring sufficient learning [50]. Key parameters included a predefined learning rate, an optimizer, and a categorical cross-entropy loss function.

2.4.2. Model Evaluation

The evaluation focused on measuring accuracy and loss using the test dataset to determine the model's effectiveness in classifying unseen images. TensorFlow Lite Model Maker's built-in features facilitated monitoring of key performance metrics and visualization of training progress, allowing real-time parameter adjustments.

The model achieved 90% accuracy on the test set, demonstrating its ability to generalize from learned patterns. Detailed visualizations of the training history were generated, and a confusion matrix was employed to evaluate the model's performance in classifying each plant type, providing insights into its strengths and weaknesses across different categories. The process described in the methodology is graphically illustrated in Figure 3.

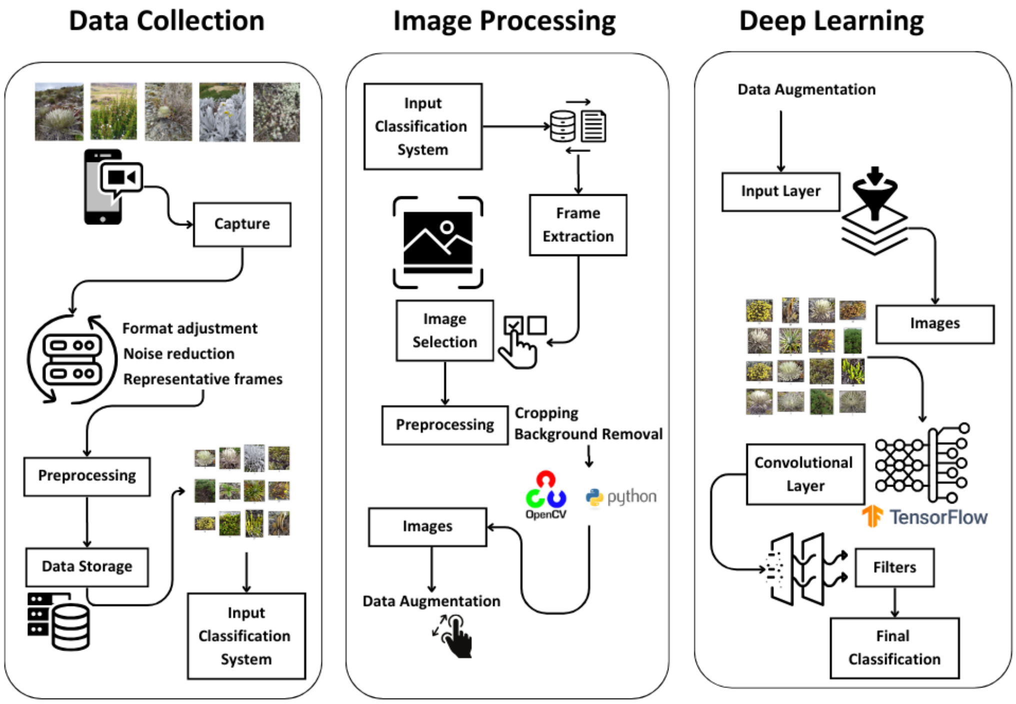


Figure 3. Block diagram of the proposed process.

3. Results

The model was trained and evaluated using the Spyder interpreter within an environment configured with Anaconda Navigator, employing Python 3.7, TensorFlow 2.9.3, Model Maker 0.4.2, OpenCV 4.8.0, Scikit-Learn 1.2.0, and the Keras 2.9.0 library on an Intel Core i5 CPU. The tests of the convolutional neural network (CNN) model were conducted on a system with the following hardware specifications: Intel® Core™ i5-6400 CPU (2.70 GHz), 16 GB of RAM, and Windows 10 Pro, version 2H2. This system provided the computational foundation for training and evaluating the model. The process was executed without GPU acceleration, relying solely on the processor and available RAM.

Prior to model training, the plant image dataset was divided into three subsets: training, validation, and testing [51]. The training subset, comprising 1200 images distributed across 12 classes, underwent normalization and resizing to 224 $\times$ 224 pixels to meet the model's requirements [52]. The validation and testing subsets each contained 100 images, and for model training, 400 images per class were utilized with data augmentation techniques [53]. The training environment was configured, and the EfficientNet Lite4 model was trained with the prepared dataset, achieving the target accuracy within 10 epochs.

Figure 4 depicts the training and validation accuracy and loss curves for the EfficientNetLite4 model applied to the recognition of endemic species in the Santurbán paramo. The model shows a consistent improvement in accuracy and a reduction in loss across the epochs. The accuracy for both training and validation sets gradually increased, reaching values close to 99% after approximately seven epochs. The loss function also decreased consistently, stabilizing around 0.6 in the validation set and showing a similar trend in the training set.

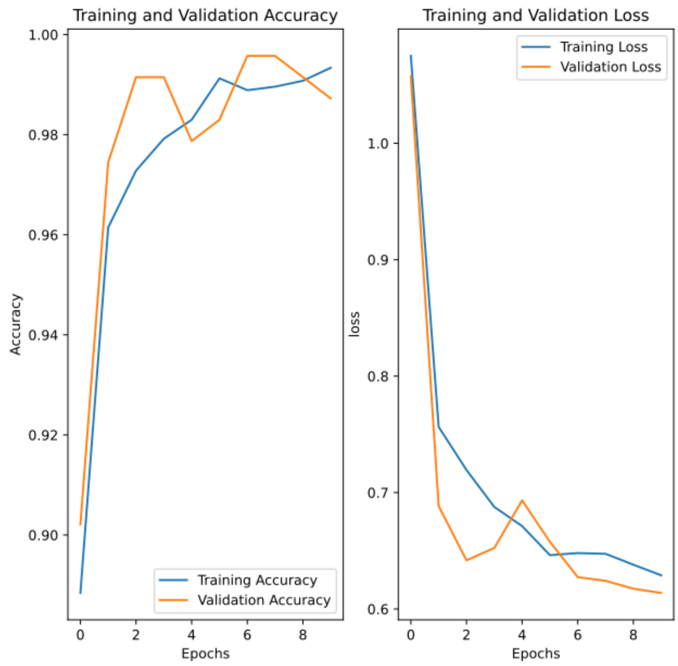


Figure 4. Performance curves of the EfficientNet Lite4 model in training and validation.

The trajectories of the training and validation curves are closely aligned, suggesting minimal overfitting. Both accuracy and loss metrics converged relatively early, with optimal values achieved before the ninth epoch. This stability and early convergence indicate that the model generalizes well from the provided data.

To evaluate the effectiveness of the model in accurately identifying plant species, several standard machine learning model performance metrics were used [54], each providing a different perspective on the model's ability:

Accuracy: This metric measures the proportion of correct predictions (both positive and negative) over the total cases examined. It provides an overview of the model's effectiveness in correctly classifying plant images.

$$Accuracy = \frac{Positive\ true + negative\ true}{Positive\ true + negative\ true + false\ positive + false\ negative}$$

Sensitivity (Recall): Also known as true positive rate, it measures the model's ability to correctly identify all true positive instances of each species. It is essential to ensure that the model does not fail to identify species present in the images.

$$Sensitivity = \frac{True\ positive}{True\ positive + false\ negative}$$

Specificity: This metric measures the proportion of true negatives correctly identified relative to the total true negative cases. That is, it indicates how well the model can identify non-occurrences of a specific condition. The formula to calculate Specificity is

$$Specificity = \frac{True\ negative}{True\ negative + false\ positive}$$

Precision: Calculates the proportion of correct positive predictions (true positives) to the total positive predictions made (including true and false positives). This metric is crucial in determining how reliable the model's identifications are when classifying an image as belonging to a specific species.

$$Precision = \frac{True\ positive}{True\ positive + false\ positive}$$

F1 Score: Represents the harmonic mean between Precision and Sensitivity, providing a balance between both metrics. It is especially useful when an evaluation that considers both the precision and the complete recovery capacity of the relevant species is desired.

$$F1\ Score = \frac{2 * True\ positive}{2 * True\ positive + false\ negative + false\ positive}$$

The confusion matrix and classification reports from [55] were employed to analyze the model's performance in identifying endemic plants of Santurbán. Figure 5 presents the confusion matrix, illustrating the correct and incorrect classifications by species, with rows representing actual categories and columns representing the model's predictions. The main diagonal indicates the number of correct classifications, while off-diagonal cells reflect misclassifications.

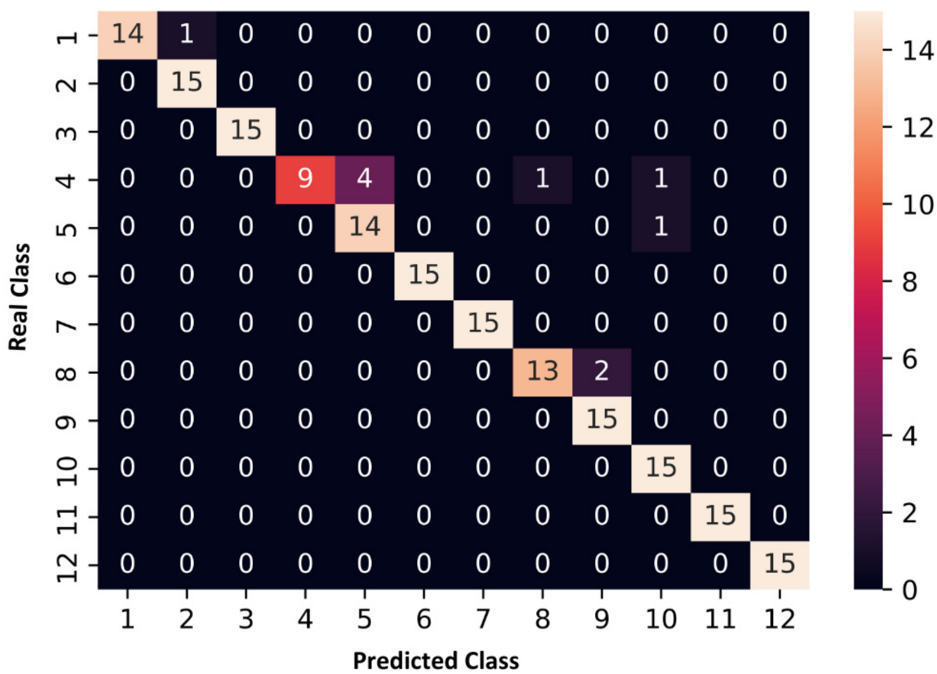


Figure 5. Confusion matrix of the EfficientNet Lite4 model.

In Figure 5, it is observed that the model correctly classifies the majority of images into their respective classes. Each class has at least 13 instances correctly classified, with several reaching the maximum classification of 15 instances. The few misclassifications are evident in the non-diagonal cells with non-zero values. This indicates that the EfficientNet Lite4 model effectively distinguishes between classes, although some minor confusions between adjacent classes are present, possibly due to similarities in the visual characteristics of the images within those classes.

This analysis allows for evaluating the EfficientNet Lite4 model's ability to classify different plant species, enhancing the understanding of its performance and identifying areas for improvement and optimization in practical applications.

FloraBan: Mobile Application for Flora Identification in the Santurbán Paramo

FloraBan is a mobile application for Android devices developed using the Flutter framework. It employs machine learning algorithms to identify endemic plant species of the Santurbán paramo from images captured with the device's camera or selected from the user's gallery. The application processes these images using the Google_ML_Kit library, which implements image classification models. By comparing the extracted features from the pictures with an internal database containing information on 12 native flora species of the Santurbán paramo, FloraBan identifies the plant species and provides a detailed fact sheet, including the common name, scientific name, family, genus, description, region, and conservation status. This detection and classification process is illustrated in Figure 6.

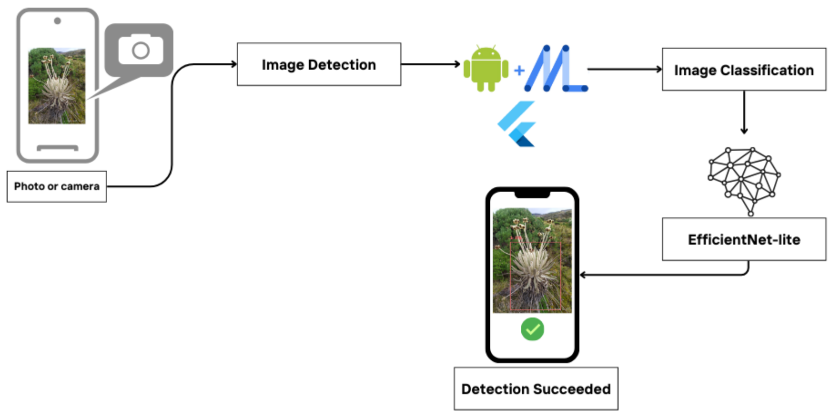


Figure 6. Plant detection and classification process in the FloraBan application.

The user interface of FloraBan is designed to be simple and intuitive, facilitating easy navigation and access to image capture, result display, and species information features (Figure 7). The technical implementation incorporates the EfficientNet Lite4 model, which enables predictions in approximately one second. This process, covering detection and classification and displaying detailed information stored in the app's internal database, functions autonomously without requiring an internet connection. Tests conducted with close-up images of plants against various natural backgrounds demonstrated an accuracy exceeding 85% for certain plant classifications. Figure 7 presents a photo taken in the field within the Santurbán paramo, showcasing the application's performance in predicting plant species, with results for each studied species detailed in Table 3.

a) Application home screen and Image capture screen

Figure 7. *Cont.*

b) Image analysis result screen and Detailed information section

Figure 7. Screenshots of the FloraBan application interface. (**a**) Application home screen and image capture screen. (**b**) Image analysis result screen and detailed information section.

Table 3. Results of Floraban in the field.

Identification	Scientific Name	Confidence Level
1	*Espeletia boyacensis Cuatrec* [31]	85
2	*Espeletia conglomerata A.C.Sm* [31]	91
3	*Senecio niveoaureus Cuatrec* [32,33]	92
4	*Arcytophyllum thymifolium (Ruiz & Pav.) Standl* [34]	76
5	*Monticalia vernicosa (Sch.Bip. ex Wedd.) C.Jeffrey* [35]	78
6	*Acaena cylindristachya Ruiz & Pav* [36]	87
7	*Puya asplundii L.B.Sm* [37]	88
8	*Hypericum juniperinum (L.fil.) Kunth* [38]	88
9	*Alchemilla alpina* L. [31]	82
10	*Disterigma empetrifolium (Kunth) Nied. ex Drude* [39]	78
11	*Lycopodium clavatum* L. [40]	70
12	*Elaphoglossum engelii (H.Karst.) Christ* [41]	78

The application's system architecture is built on Flutter, which facilitates the development of native interfaces for Android. Data exchanges are managed locally on the device, utilizing the "google_mlkit_image_labeling" API for image processing, JSON format for data structuring, and TensorFlow Lite for executing the machine learning model. The prediction mechanism in FloraBan employs custom TensorFlow Lite models to classify plant images, with predictions being validated through a threshold that determines the minimum probability required for a prediction to be considered accurate.

FloraBan serves as a valuable tool with applications in scientific tourism, environmental education, and research within the Santurbán paramo. Its ability to quickly and accurately identify plant species contributes to the knowledge and conservation of biodiversity in this ecosystem.

4. Discussion

The data collection in the Santurbán paramo, conducted over four months, involved visits to key tourist sites representative of the local ecosystem, such as Laguna Negra and Laguna Pajarito. These efforts were crucial for capturing images and videos that simulate the visual conditions and perspectives of tourists, which are essential for developing a dataset that accurately reflects the biodiversity of the paramo [56]. However, it is important to consider that the use of a mobile phone for video capture, while accessible and practical, might limit the quality and diversity of the images due to the inherent limitations of these devices.

In the subsequent processing of the images, Python tools were used to extract representative frames from the videos, thereby creating a diversified photographic database. This approach aligns with the discussion by Afzal et al. [57], who emphasize the importance of visualization and visual analytics techniques for handling complex image and video datasets. However, the process of manually segmenting and cropping the images, although necessary to ensure the accurate representation of plant species, introduces a layer of subjectivity that could influence the model's outcomes.

Data augmentation techniques, such as flipping, mirroring, and rotation, were applied to increase the number of images per species (from 100 to 400), thereby strengthening the dataset and enhancing the model's ability to handle variations in species appearance under different conditions [53]. While these techniques are valuable, they must be carefully considered to avoid the model overfitting to artificial transformations, as discussed in the literature.

Regarding the implementation of the EfficientNet Lite4 model, which was selected for its efficiency on mobile devices, TensorFlow Lite was utilized to ensure optimal performance on mobile platforms. This approach is supported by Bursa et al. [58], who demonstrated how TensorFlow Lite can reduce computational load without sacrificing accuracy. The validation of the model, which included the use of a confusion matrix and manual testing with previously unseen images, underscores the importance of comprehensive evaluation that complements automatic metrics with practical testing.

This discussion highlights the necessary balance between methodological rigor and practical applicability. While the data collection and processing strategies are well founded, it is also crucial to consider how these decisions impact the model's reliability and applicability in diverse environments. The choice of an efficient model for mobile devices, as emphasized in the work of Bursa et al. [58], is particularly relevant in contexts where computational resources are limited, but it requires ongoing evaluation to ensure that these optimizations do not compromise the model's versatility and effectiveness in real-world applications.

The EfficientNet Lite4 model, selected for its balance of accuracy and computational efficiency, demonstrated an accuracy exceeding 90% in the classification of plant species under controlled conditions [27,49]. This success is largely due to the model's architecture, which employs a compound scaling method to optimize network depth, width, and resolution simultaneously, ensuring both accuracy and efficiency [43] However, the model's performance is challenged in natural environments where species exhibit similar morphological characteristics or are subject to complex lighting and background conditions [27,49]. These challenges are common in automated plant identification, where environmental factors such as shadows and varying distances can impact accuracy.

To mitigate these challenges, it is crucial to diversify the training dataset by including images captured under various environmental conditions and phenological stages of the plants. This approach would enhance the model's ability to adapt to the variability inherent in natural settings, thus improving its robustness and accuracy. Additionally, advanced image processing techniques, such as lighting correction, noise reduction, contrast enhancement, and image segmentation, can further refine the model's ability to distinguish between species by highlighting distinctive features and minimizing the influence of external elements.

Moreover, integrating attention mechanisms, as suggested by Chen et al. (2021) [59], could further improve the model's ability to focus on the most informative regions of the image, thereby enhancing its discriminatory power. These strategies, combined with the inherent efficiency of the EfficientNet architecture, are essential for ensuring the model's robustness and accuracy in real-world applications.

The FloraBan platform is a pivotal tool for promoting sustainable tourism and managing biodiversity in the Santurbán paramo. By educating tourists about local flora and encouraging responsible behaviors, FloraBan fosters a deeper commitment to conservation and enhances the overall tourist experience [23]. The integration of artificial intelligence (AI) allows FloraBan to offer personalized recommendations based on real-time data and individual preferences, thus tailoring the experience to each user [60]. This personalization not only improves the visitor's engagement but also promotes conservation efforts by making information relevant and accessible.

To further enhance FloraBan's impact, emerging technologies such as augmented reality (AR) and virtual reality (VR) can be incorporated. AR can overlay educational content about plant species directly onto the user's view of the paramo, while VR offers virtual tours that engage users before they even arrive at the site, setting realistic expectations and fostering a greater appreciation for the environment [61]. These technological enhancements can help guide tourists through environmentally sensitive areas, providing real-time alerts about ecological concerns and suggesting alternative routes to minimize their impact [62,63].

Moreover, the integration of these technologies into FloraBan strengthens the connection between tourists and the natural environment, leading to increased environmental awareness and responsible behavior. As tourists interact with the paramo through FloraBan, they become more invested in its conservation, thereby supporting long-term sustainability goals [64,65].

The integration of emerging technologies into conservation efforts offers significant potential for enhancing the effectiveness of biodiversity management in the Santurbán paramo. Tools such as augmented reality (AR), virtual reality (VR), and Internet of Things (IoT) devices enable more interactive and personalized tourism experiences, aligning tourist expectations with the realities of the environment and promoting responsible behavior [61,66].

Providing tourists with real-time information about the ecological sensitivity of areas within the paramo is a key strategy for minimizing environmental impact. By using technologies that deliver current environmental data, FloraBan empowers tourists to make informed decisions, helping to protect delicate ecosystems while enriching their experience [62,63]. Additionally, these technologies can strengthen the relationship between tourists and local communities by promoting sustainable practices that are culturally and environmentally appropriate [63].

Long-term monitoring is essential for tracking the health of plant populations and the broader ecosystem. Technologies such as remote sensors and satellite imagery facilitate continuous monitoring, allowing for the early detection of ecological changes and the timely implementation of conservation measures [67,68]. Involving local communities in this process is crucial, as their insights and daily observations can provide valuable context to the technical data, ensuring a more comprehensive approach to conservation [69]. The success of these efforts depends on robust institutional support and regulatory frameworks that sustain conservation initiatives over time [67].

5. Conclusions

The study successfully developed and integrated the FloraBan mobile application, utilizing artificial intelligence for flora identification in the Santurbán paramo. The image and video collection process in this unique environment presented challenges that were carefully addressed. Image segmentation and data augmentation were employed to prepare a robust dataset for training the plant identification model.

The selection of the EfficientNet Lite4 model was driven by its balance of accuracy and computational efficiency, making it suitable for mobile device implementation. The use of TensorFlow Lite ensured the model's smooth execution within the application, contributing to a user-friendly experience.

FloraBan has the potential to contribute to both tourism and biodiversity conservation in the Santurbán paramo. By providing tourists with a real-time plant identification tool, the application enhances their interaction with the local environment and fosters a deeper understanding of the region's biodiversity. Additionally, FloraBan can serve as a valuable resource for researchers and citizen scientists, facilitating the collection and analysis of data related to plant distribution and abundance, which is crucial for conservation efforts.

The model's performance in field conditions, however, is affected by factors such as lighting variability and complex backgrounds. These limitations highlight the need for expanding and diversifying the training dataset to encompass the range of conditions encountered in natural environments. Future research should explore advanced preprocessing and data augmentation techniques to enhance the model's robustness and accuracy in real-world applications.

Furthermore, there is potential to further develop the application by integrating additional features such as geolocation tracking and social sharing options. These enhancements would improve the user experience and encourage greater engagement with the application, thereby supporting responsible and educational tourism practices.

In conclusion, FloraBan represents a notable advancement in the application of artificial intelligence for biodiversity conservation and the promotion of sustainable tourism in sensitive ecosystems like the Santurbán paramo. While the current version of FloraBan has demonstrated its effectiveness in controlled settings, ongoing improvements, and future research are necessary to ensure its success in more challenging, real-world environments. The continued development and refinement of this tool will contribute to the preservation of critical natural habitats and the promotion of ecological awareness among both tourists and the local community.

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