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Investigating cultural ecosystem services of the Caatinga on Flickr

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ABSTRACT

Public interest in nature can be promoted through social media by assessing the importance of a species to people and identifying new emblems appealing to conservationists. We aimed to assess the public interest in cultural ecosystem services in the Caatinga (seasonal dry forest). Ecosystem services were categorized on approximately 1500 photographs posted on Flickr. These photographs were analyzed using manual and deep-learning (DL) approaches. The most observed categories for both approaches were "Enjoyment of the Landscape" (36.8%), "Appreciation of Nature – Animals" (25.6%), and "Social Activities" (19.3%). However, we found significant differences between the manual and DL classifications, owing to the difficulties in classifying categories using the DL model. These findings suggest low cultural ecosystem service representation on the photo-sharing platform Flickr in the Caatinga region, even after removing 67% of the collected data. This may be attributed to the limited interest in Flickr among the Caatinga residents. Deep learning techniques have the potential to study cultural ecosystem services, but their efficacy depends on the capacity of the algorithm to discern human-nature interactions and various natural elements. Our observations indicate that increasing the scale of the training and test datasets and incorporating additional categories to account for Caatinga diversity may enhance the results.

Keywords: Caatinga, Culturomics, Conservation, Flickr, Ecosystem Services, Social Network.

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SIGNIFICANCE STATEMENT

This study leverages the power of social media and advanced deep learning techniques to explore and evaluate public interest in the cultural ecosystem services of the Caatinga, a unique and biodiverse semi-arid region of northeastern Brazil. This research underscores the potential of integrating social media data and artificial intelligence in environmental monitoring and conservation strategies, offering a novel approach to understanding and promoting the natural heritage of lesser-known ecosystems such as the Caatinga.

INTRODUCTION

Caatinga, a semi-arid region in northeast Brazil, is home to rich biodiversity and high endemicity (Leal *et al.* 2005). However, its diversity is threatened by various factors, particularly by climate change (Bragagnolo *et al.* 2017). Lessa *et al.* (2019) highlighted the challenges in conservation planning in the Caatinga, emphasizing the need for more information, financial and educational incentives, and improved working conditions. These issues highlight an urgent need for innovative conservation strategies.

The Internet, a ubiquitous tool in most countries, hosts social media platforms that contain vast amounts of digital data, including interactions between people and their environments (Di Minin *et al.* 2015). Social media, a web-based service that fosters collaboration, connection, and interaction, can be a powerful tool for monitoring the public interest in the Caatinga and its ecosystem. The potential of social media and online platforms as valuable tools for biodiversity conservation is inspiring (Alves *et al.* 2019; Begin *et al.* 2018; Morcatty *et al.* 2020; Borges *et al.* 2021, 2022; Gippet *et al.* 2023). However, their utilization can be challenging because of the lack of freely available methodologies and permissions for accessing social network data (Ghermandi and Sinclair 2019).

Ecosystem services, which are natural support systems that sustain human life, encompass the fundamental benefits generated by ecosystems (MMA, 2022). These services are categorized as regulation and maintenance, provision, and cultural, with the latter being particularly relevant for assessing the public interest. Cultural ecosystem services (CES) provide non-material benefits to nature, such as recreation, fun, aesthetics, and spirituality (Bragagnolo *et al.* 2017). Therefore, this is a key focus of this study.

Automated classification models using deep learning (DL) techniques have been proposed as tools for assessing the public interest in CES (Havinga *et al.* 2021; Cardoso *et al.* 2022). DL, a class of machine learning techniques, involves learning multiple levels of representation and abstraction to make sense of data such as images, sounds, and text (Almeida *et al.* 2018). In our study, we used DL to create a computational model for image classification, specifically a type known as a convolutional neural network (CNN), which can identify similarities in an image's information content, similar to that of a biological brain (Cardoso *et al.* 2022).

This study aimed to identify the cultural ecosystem services (CES) that generate the most interest among social media users and evaluate the feasibility of utilizing social media and deep learning to gather data on public interest in the Caatinga region. In particular, we manually identified CES in Caatinga using Flickr posts and assessed the feasibility of using DL techniques. Conservation Culturomics is a methodological approach to studying human culture using large digital bodies. It seeks to understand the human–nature relationship and identify various aspects of this relationship (Ladle *et al.* 2016). Such approaches are helpful in assessing the public interest in ecosystems, as we aim to do in this study. Social media can be a powerful tool for demonstrating and promoting public interest in nature, the importance of a species to people, and new flagship species and conservationist emblems.

MATERIAL AND METHODS

Data for the analysis were collected using the social network Flickr (www.flickr.com), which was selected because of its large geographic reach and wide access to photographs and videos posted globally (Retka *et al.* 2019). Flickr has been widely used in other CES studies (see Mouttaki *et al.* 2022; Ciesielski & Stereńczak 2021).

Human–nature interactions are associated with analyses at large spatial and temporal scales; however, analyses of social media content in the context of CES are based on the manual classification of images or texts shared by social media users (Cheng *et al.* 2019; Retka *et al.* 2019). In this context, we used two approaches for classification: manual classification based on visual analysis of photographs, and DL classification. We used the descriptions cited for each CES as the selection criterion for manual classification. We created an image classification model for DL classification that categorized the data based on training, using data similar to the analyzed categories. Image classification using a computational model is a complex process, and its accuracy is mainly related to the dataset characteristics, complexity of the problem under analysis, and the robustness of the classification algorithm (Colkesen & Kavzoglu 2019).

Categories analyzed

The categories analyzed in this study were adapted from those of other similar studies (Richards & Friess 2015; Jepson *et al.* 2017; Retka *et al.* 2019). The category "Appreciation of Nature" was split into two categories: one focusing on plants and the other focusing on animals. The "Landscape Appreciation" category (photographs focused on broad, large-scale views of the landscape) includes "Natural Monuments and Structures" and "Artistic and Cultural Expression" (photographs representing artistic and cultural manifestations, and products of human creation—paintings, sculptures, music, and architecture), which includes "Historic Monuments." "Social Activities" (photographs focusing on groups of people engaging in social activities, whether formal or informal) includes “Social Recreation,” ”Religious or Spiritual Activities,” “Research and Education,” and “Sports Recreation.” These changes were made to reduce the data bias during classification. Therefore, we considered it more appropriate to merge some of the categories (Table 1).

Data collection

Data were downloaded using RStudio v4.1.0. (RStudio 2020 Team), with the help of the Flickr application programming interface (API) provided by Richards and Friess (2015). The API allows data collection within the social network, and returns only 500 photographs per collection. The “tags” used for the search were “Caatinga,” “Nature,” “Biodiversity,” “Landscape,” “Plants,” “Animals,” and “Culture.” These “tags” were selected to diversify the results and obtain photographs of the different ecosystem services. We executed a procedure to retrieve geotagged and non-georeferenced photographs by using identical tags posted by Flickr users in Brazil between 2012 and 2022. The aim was to gather a large quantity of data for analysis. The photographs were stored in a designated directory on the drive. Prior to the analysis, the data underwent a cleaning process that involved the removal of photographs that did not conform to the selected criteria for each category and duplicated images. Of the 1,500 photographs collected, 488 were analyzed. During the cleaning process, we discovered that approximately 68% of the images were repeated because Flickr API failed to filter the gathered data.

Classification model with deep learning

For the image classification model, we adapted the script reported by Doust *et al.* (2021) by using Google Collaboratory (`https://colab.research.google.com`). The image classification model consists of data preprocessing and standardization, convolutional neural network (CNN), training, and validation. First, we defined a set of images for training and another for validation. This set of images was obtained from browsers such as Google (www.google.com) and Bing (www.bing.com) using keywords referring to each category together with the words “Caatinga” or “Sertão’ or “Northeast” (e.g., Appreciation of the Landscape = “Caatinga Landscape”). For training, 650 photographs were collected; for validation, 225 photographs were collected. The training and validation phase of the model is one of the most important because, in the training phase, the model learns what each selected category represents. In the validation phase, the model tested the knowledge learned in a database that differed from the training dataset. The classification of the data under analysis was based on what was taught by the training bank, and was collected following the criteria described for each category. We used the TensorFlow (Abadi *et al.* 2016), Matplotlib (Hunter 2007), Numpy (Harris *et al.* 2020), PIL (Clark 2015), and Keras (Chollet *et al.* 2015) packages.

The model starts with data preprocessing, which analyzes the number of pixels in photographs. The data were then standardized to create a pattern for the image size. The main point of the model is formed by a CNN, which has layers that simulate groups of neurons, detect the attributes of the presented image, and organize them hierarchically and in an abstract manner to generate information (see Cardoso *et al.* 2022). When the CNN was ready, the model went through the learning phase with the training dataset, and then the test phase with the validation dataset. After these two phases, we printed graphs showing model performance (accuracy and loss).

Transfer learning is a learning method that involves using knowledge learned to solve different problems (Utsch 2018). In this case, the problem would be to understand public interest in the CES in Caatinga. We added data augmentation and abandonment functions to avoid overfitting, which occurs when the model learns from unwanted details of the trained images and can only categorize the training data well, thereby affecting efficiency (Doust *et al.* 2021). Finally, we added the data for analysis as a directory to perform the sorting.

Comparison of classification methods

We conducted a comparative analysis of the rankings using RStudio version 4.2.1 (RStudio 2020) and organized the outcomes in a contingency table. Subsequently, Pearson’s chi-square test was performed. If the obtained chi-square value was statistically significant ($p < 0.05$), a post-hoc analysis was conducted to ascertain the specific categories that exhibited significant differences. We selected this test because it allows us to determine the extent of similarity or dissimilarity between the methods and helps to identify the categories contributing to the observed differences.

Table 1. Categories of Cultural Ecosystem Services (CES).

Categories (CES)	Description of photos
Nature Appreciation - Animals	Animal-focused photos.
Nature Appreciation - Plants	Photographs with a focus on plants.
Landscape Appreciation	Photographs whose main focus is a broad and large-scale view of the landscape.
Social Activities	Photographs focusing on groups of people in social activities, whether formal or informal.
Artistic and Cultural Expression	Photographs representing artistic and cultural manifestations, and products of human creation.

Table 2. Number of photographs in which each cultural ecosystem service (CES) was observed, using the Manual classification and the classification with Deep Learning (DL).

CES	Manual Classification	DL Classification
Nature Appreciation - Animals	125	135
Nature Appreciation - Plants	65	47
Landscape Appreciation	180	125
Social Activities	94	58
Artistic and Cultural Expression	24	123
Total	**488**	**488**

RESULTS

Manual classification of the photographs revealed that the category "Appreciation of the Landscape" was present in 36.8% of the photographs, "Appreciation of Nature - Animals" in 25.6%, "Social Activities" in 19.3%, "Appreciation of Nature - Plants" in 13.4%, and "Artistic and Cultural Expression" in 4.9%. The results of the analysis using the image classification model revealed that "Appreciation of Nature - Animals" was present in 27.7% of the photographs, "Appreciation of the Landscape" in 25.6%, "Artistic and Cultural Expression" in 25.2%, "Social Activities" in 11.9%, and "Appreciation of Nature - Plants" in 9.6% (see Table 2).

A comparison between the classification approaches using the chi-square test demonstrated that the results differed significantly ($\chi^2 = 84.535$, $p < 0.0001$). In the post-hoc analysis, we observed that the "Landscape Appreciation" ($p < 0.005$) and "Artistic and Cultural Expression" ($p < 0.05$) categories were significantly different between the manual and DL approaches.

The DL model achieved an accuracy of 100% using the training data and 59% using the validation data (Figure 1). After the data increase and abandonment functions, the model achieved 100% accuracy in training and 63% accuracy in validation (Figure 2).

DISCUSSION

CES in Caatinga

The category "Landscape Appreciation" emerged as the most frequently observed cultural ecosystem services (CES) in both categories, which is consistent with findings from previous studies (Cardoso *et al.* 2022; Mouttaki *et al.* 2022). The most photographed landscapes were those from the Catimbau National Park in Pernambuco and Serra da Capivara in Piauí, both in NE Brazil.

The second most popular category was "Appreciation of Nature - Animals," and most of the animals captured in the photos were birds, including *Nyctidromus albicollis* and *Anodorhynchus leari*. Mammals, such as *Callithrix jacchus*, were also visible in the background. This interest in animal life may be attributed to scientific studies, human use, or aesthetic value.

The third most frequently observed category was "Social Activities," indicating the importance of

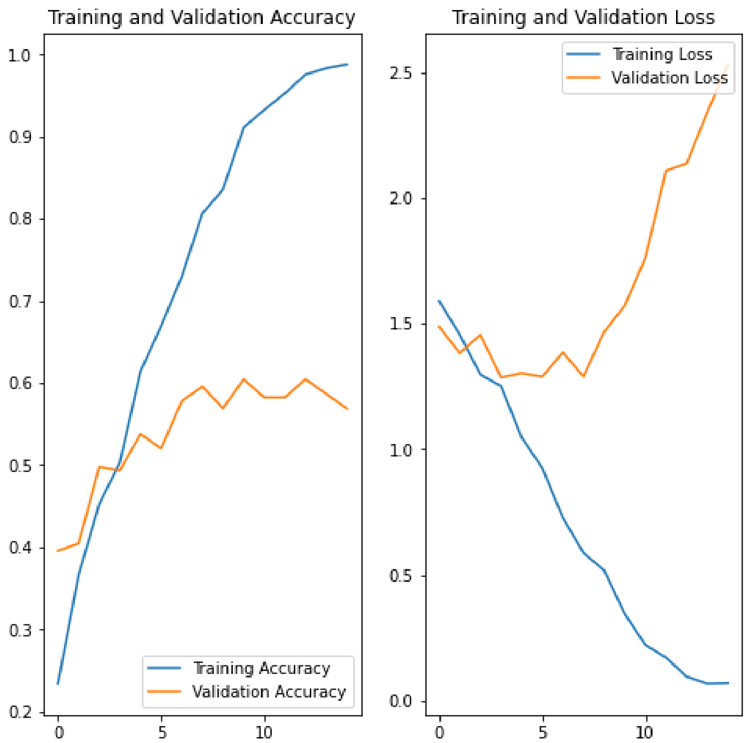

Figure 1. Efficiency of the Deep Learning model.

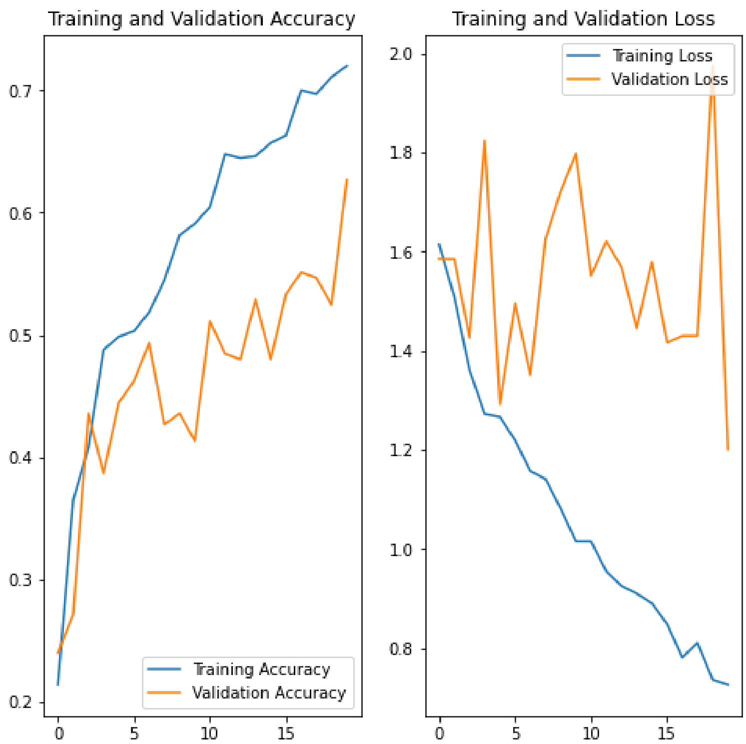

Figure 2. Efficiency of the Deep Learning model with data augmenting and abandoning functions.

human-nature interaction in our development. Religious and educational initiatives and group activities, such as village gatherings, hiking, fishing, and cycling, were common in the observed photographs.

The category "Appreciation of Nature - Plants" ranked fourth, with most of the captured plants being cacti such as *Melocactus zehntneri*, *Opuntia cochenillifera*, *Cereus jamacaru*, and tree species such as *Spondias tuberosa* and *Ceiba glaziovii*. Most photographs focus on specific parts of the plant, such as flowers and fruits.

CES are increasingly recognized as critical to conservation and sustainable development, as they provide recreational opportunities, shape human identity and traditions, and motivate conservation efforts (Di-Minin *et al.* 2015). Conservation interventions are most effective when they attract public interest and support, and culturally based metrics can inform the design of such interventions in the public dimension (Ladje *et al.* 2016). Identifying CES categories that attract public interest highlights opportunities to implement and communicate conservation policies.

Manual Classification and Deep Learning

Manual and DL sorting yielded different results, with the biggest difference being in "Landscape Appreciation" and "Artistic and Cultural Expression categories." The DL model may have been confused between the "Landscape Appreciation" category and the "Nature Appreciation" categories for animals and plants, because the photographs of the latter categories were also taken within the landscape scenes. Depending on the angle, cut, or approximation of the image, the model may have classified photographs as the "Landscape Appreciation" category when they should have been classified as the "Nature Appreciation" category. To resolve this problem, a fixed dimension must be defined in order to cut the image. When creating a training bank, photographs showing plants or animals should be omitted even if they follow the criteria defined for the category. The "Artistic and Cultural Expression" category is about the art and culture encompassing the Caatinga biome, and thus includes many varieties. Given this variety, the model may not understand the characteristics of this category. In this case, it would be interesting to divide this category into two or three subcategories, perhaps based on different cultural elements, such as paintings, sculptures, and historical monuments (e.g., churches and squares), and artistic elements, such as dance, music, and popular festivals. Separating and homogenizing the aspects of the subcategories may avoid confusion.

Despite the difference in results between the model and DL sorting, the overall efficiency of the DL model was 59–63% because the model behaved as desired for three of the five categories. The values that differed in the post-hoc analysis refer to problems during the training of the DL model, in which overfitting occurred, indicating that the model worked well for the existing data but failed to generalize to new situations. Overfitting usually occurs when the RNC architecture is highly complex (the more layers the network has, the deeper and more complex the categorization), or when the training dataset is small (ABRACD 2022). In our study, the training dataset was small compared to those used in other studies for image classification, which had at least 1000 images for training, as in the work of Zhang *et al.* (2019) and Cardoso *et al.* (2022). We observed a shortage of photographs related to Caatinga during the assembly of the training and validation sets. This negatively affected the model's classification, as its reference set was too small, thus lowering model efficiency. The model was highly accurate with the training data, but not with the validation data, as if the model simply memorized the training set without sufficiently understanding the digits to generalize to the validation set. After adding the data increase and abandonment functions, the model showed an increase in the validation accuracy. However, the results were presented nonlinearly, indicating that a larger training bank is required to obtain more accurate results.

Use of Flickr in the Caatinga

Flickr is popular among photographers and is used to upload high-quality photos using professional cameras (Di Minin *et al.* 2015). Flickr users tend to be enthusiasts of nature interested in less charismatic biodiversity groups, and are a more popular social network with more experienced tourists (Di Minin *et al.* 2013). Most of the collected photographs were repeated during data cleaning, because the Flickr API did not filter the already collected data. Our findings suggest a limited representation of the cultural ecosystem services (CES) of Caatinga. This conclusion was based on the removal of 67% of the collected data, resulting in a loss of 1,012 photographs during the cleaning process. This can be explained primarily by the fact that people living in the Caatinga do not have access to flickers. Although more than 28 million people live in the northeastern semi-arid region (Tabarelli *et al.* 2018), a large part of the region's population has little access to basic services, such as health, education, and basic sanitation, characterized by poor socioeconomic infrastructure and income from farming activities, which directly depends on the low distribution of rainfall in the region (Silva *et al.* 2017). If the population in this region does not have access to social networks, photographs of the biome will rarely be uploaded to Flickr. Another factor explaining the lack of representation may be that the Caatinga has far fewer integral protection units (29) than the other two major biomes in the country: the Amazon (112) and Atlantic

Forest (120) (MMA, 2016).

Our study corroborates the idea proposed by Moreno *et al.* (2020) that social media has the potential to be used in place of or alongside traditional surveys as a representative source of data to assess social preferences for biodiversity. However, further analysis of social networks is required to gain new insights into the public interest in Caatinga, seeking to reach more social niches and greater diversity of data. Social networks provide a rich source for studying people's activities in nature and understanding conservation debates or discussions online (Di Minin *et al.* 2015). Collaborations between conservation agencies and social media platforms should be promoted to monitor social media users visiting protected areas to develop real-time solutions that can improve visitor experiences and protected area management (Di Minin *et al.* 2015).

We consider that metrics based on digital tools and social media are still useful for supporting and evaluating CES as they measure the attributes of nature that contribute to people's aesthetics, recreational and spiritual enjoyment, and insights into how human–nature interactions change over time.

CONCLUSION

The utilization of social media has proven to be a valuable tool for comprehending societal inclinations towards CES in Caatinga. However, Flickr may not be the most appropriate platform for collecting data for this biome, as evidenced by the insufficient photographs gathered and analyzed in our investigation. Deep learning techniques may be useful in assessing CES, but their efficacy requires high complexity for identifying human-nature interactions or varied natural components. We noted that using a larger training and testing dataset and additional categories to represent the diversity of the Caatinga could produce superior outcomes in this study. Further research is necessary to advance the extraction of social media data and DL techniques.

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DATA AVAILABILITY

The data are available upon reasonable request.

CONFLICT OF INTEREST

Dr. Ulysses Albuquerque declares that he serves as a Co-Editor-in-Chief for Ethnobiology and Conservation and has removed himself from the peer-review process for this paper.

CONTRIBUTION STATEMENT

Conceived of the presented idea: UPA, DVBO
Collected the data: MVAS, DVBO
Interpreted the data: UPA, DVBO, MVAS
Wrote the first draft of the manuscript: MVAS
Review and final write of the manuscript: UPA, DVBO

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