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Artificial intelligence improves the identification of fur seals recorded at Southern Brazilian coast

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Abstract

The genus *Arctocephalus* represents the group of fur seals that mainly inhabit the Southern Hemisphere. In general, *Arctocephalus* species are extremely similar in appearance, often making it very difficult to impossible to distinguish them only by characteristics of their external morphology. In this context, it is important to find new tools to differentiate them, especially in locations outside of their traditional distribution area, such as Brazilian waters, in order to take appropriate actions for their management. This study proposes the use of an artificial intelligence method, based on machine learning and convolutional neural networks, to classify and identify three species of southern fur seals by analysing 121 facial images from living specimens of *Arctocephalus australis*, *A. gazella*, and *A. tropicalis* found on the Brazilian coast. The image database was created using only images of the faces of adult males, which presented more conspicuous diagnostic characteristics of each species. The images were randomized and divided into 70% for training (26 images of South American fur seal, 30 of sub-Antarctic fur seal, and 29 of Antarctic fur seal) and 30% for testing (12 images of each species). The convolutional neural networks identified patterns in the pixels of the images provided for training and testing procedures. These patterns allowed the generation of recognition algorithms, which led to the classification of images by probability into one or another species. The generated model correctly classified 83.34% of the images attributed to the test, suggesting high accuracy in this classification. However, it is important to explain that the model does not identify morphological diagnostic characters that distinguish the fur seals species, it only recognises patterns in image pixels. These results could be integrated into a citizen science platform in a mobile phone app that allows the general public to identify the *Arctocephalus* species found on the Brazilian coast and contribute to the knowledge of local marine biodiversity.

Keywords:
citizen science convolutional neural networks, machine learning, pinnipeds.

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Introduction

The genus *Arctocephalus* belongs to the group of pinnipeds, mammals from the order Carnivora that includes the families Otariidae (sea lions and the fur seals), Odobenidae (walrus), and Phocidae (true seals and elephant seals) (Berta et al., 2006). Pinnipeds were traditionally considered as the suborder Pinnipedia (Jefferson et al., 2015), but are currently classified within the Caniformia suborder (Hedges et al., 2015). Individuals of the genus *Arctocephalus* mainly inhabit the Southern Hemisphere, with the exception of Guadalupe fur seal (*Arctocephalus townsendii*) which occurs in Mexican waters. Repenning et al. (1971) reviewed anatomical characteristics of *Arctocephalus* and recognized eight extant species of fur seals from the genus. However, it can be generally stated that *Arctocephalus* species are extremely similar, often making it very difficult, and sometimes impossible to distinguish them only by characteristics of external morphology (Bonner, 1981; Goldsworthy et al., 1997). The correct identification of some specimens is further complicated by high intraspecific variability resulting in some specimens appearing more similar to the original description than others (King, 1983). Although *Arctocephalus* species are not considered cryptic, at least in terms of internal morphology (*e.g.*, skull and teeth shape, size), some of the eight species have extremely similar external morphology (fur and morphometrics) with the exception of the sub-Antarctic fur seal (King, 1983; Goldsworthy et al., 1997). The correct identification of *Arctocephalus* species is of great significance for their conservation and for establishing the boundaries of their dispersion (Milmann et al., 2019; Sousa-Lima et al., 2022). Therefore, it is important to be able to differentiate these species, particularly by common citizens, and in locations outside their usual distribution, such as the coast of Brazil.

In southern Brazil, primarily in the state of Rio Grande do Sul (RS), three species of *Arctocephalus* have been documented: the South American fur seal (*A. australis*), the sub-Antarctic fur seal (*A. tropicalis*), and the Antarctic fur seal (*A. gazella*) (Pinedo, 1990; Oliveira, 2013; Prado et al., 2016). Among the fur seals, the South American fur seal is the most frequently sighted on the coast of RS (Oliveira, 2013). Its occurrence is considered seasonal because it has only been sighted during austral autumn and spring months. This seasonality has been associated with post-breeding foraging trips from its closest breeding colonies located in Uruguay, with these movements favoured by the cold Falklands Current (Pinedo, 1990; Simões-Lopes et al., 1995; Oliveira, 2013). Antarctic and sub-Antarctic fur seals recorded in the Brazilian coast were often considered vagrants because their arrivals are occasional in the region and completely out of the range of their traditional distribution (Oliveira et al., 2001, 2024; Ferreira et al., 2008).

The scientific community relies on updated information about species distribution and accurate data on ecosystems to develop effective management plans and conservation strategies (Goodwin et al., 2022). A promising approach to meet this need is the integration of citizen science with advanced image recognition and classification tools. These tools enable researchers to collect data on the geographical distribution of species without the need for capture, thus reducing environmental impact. This approach results in more comprehensive datasets, containing images, videos, audio, and information on the spatial distribution of species. Furthermore, it allows for improving classification accuracy and reducing error rates in models through the incorporation of these new data generated (Lopez-Vazquez et al., 2020; Goodwin et al., 2022). Ultimately, this integration of citizen science and imaging technology not only strengthens the scientific knowledge base, but also empowers the scientific community to develop more efficient management plans and conservation strategies, based on comprehensive and accurate data.

In recent years, the role of the public in science, known as "citizen science ", has grown due to the cooperation in biodiversity identification and scientific research, with widespread media coverage and academic recognition (Haklay, 2015). In the digital age, technology, such as the online availability of scientific literature and the use of citizen science platforms, has become essential for accessing biological information and extracting the records of species occurrence from electronic databases available on the internet (Newbold, 2010). As examples, iNaturalist (inaturalist.org) and the Wild Me project (https://www.wildme.org/) are platforms that combine structured wildlife research, artificial intelligence, citizen science, and computer vision to accelerate population analysis, with the aim of developing new strategies to combat biodiversity extinctions, among many other projects. Moreover, they seek to involve the general public to expand the database and make society more engaged, informed, and concerned about biodiversity conservation. According to Larson et al. (2016), citizen science can increase public awareness and understanding of certain issues, increasing engagement and interest from the population. Therefore, through citizen science, we can generate more engagement from the population towards the genus *Arctocephalus*. This way, society can also become concerned with the conservation of these species.

In addition to the increasing role of citizen science, there have been significant advancements in observation methods driven by improvements in technology that have led to the development of various tools. Moreover, several research fields are experiencing rapid transformations thanks to the utilization of Artificial Intelligence (AI) for data interpretation (Goodwin et al., 2022). Among these interpretation techniques, "machine learning" (ML) has garnered considerable attention in the scientific community. ML involves computer-based pattern recognition solely based on the data it receives. Deep learning, a commonly used method within ML, particularly stands out for its effectiveness in image recognition and classification, as demonstrated in various image classification processes in recent years (Zhang et al., 2018). These technological advancements further enhance the capabilities of citizen science and digital tools in accessing biological information and extracting species occurrence records from online databases, reinforcing their crucial role in contemporary scientific research (Goodwin et al., 2022).

Convolutional Neural Networks (CNNs) are particularly suitable for image analysis as they use computer vision to enable the detection of complex patterns from the image pixels. The network first identifies low-level features in the input image, such as small edges, patches of colour, and the like. These low-level features are then combined to form higher-level features, such as parts of ears, eyes, and so on. Meanwhile, Artificial Neural Networks (ANNs) complement this procedure by processing this information. An ANN is a set of networks inspired by the human brain with artificial neurons and synapses that are trained to approximate an external function, typically mapping input data (such as images) to labelled values or predicted categories (Goodwin et al., 2022). Therefore, the ANN algorithms learn to associate labels with examples (Christin et al., 2019). Eventually, the presence or absence of a higher-level characteristic described above contributes to the final probability generated by the neural network for any output class, aiding in the identification of the fur seals species mentioned in this study (Gareth et al., 2013).

An important limitation of CNN and ANN models is their reliance on large amounts of training data. Learning a complex pattern requires more data than learning a simpler pattern. However, reducing the lack of data can be achieved by using an existing model with pre-trained weights, which have been trained on other data sources such as the VGG16 database (Simonyan & Zisserman, 2014). This process, known as transfer learning, enables researchers to leverage large datasets readily available, like VGG16, and apply them to datasets that appear highly unrelated to the dataset of interest (Goodwin et al., 2022). By employing this method, it is possible to leverage knowledge gained from previous tasks and efficiently apply it to new problems, thus reducing the need for large volumes of specific training data for a particular application.

Considering the difficulty of differentiating fur seals of the genus *Arctocephalus* due to their similar external morphology and to help their identification by non-scientists in areas that several species could occur, this study proposed the use of Artificial Intelligence method based on CNN and ANN to classify/identify three species of southern fur seals found in the southern Brazilian coast from facial images. It is important to emphasize that the model does not identify diagnostic morphological characters that distinguish between the species, but rather patterns in the pixels of the images related to areas of color and small edges combined to form these higher-level characteristics.

Methods

Analysed material

For this study, a CNN model was used, consisting of convolutional layers for pattern extraction and an ANN for classification of images of three species of fur seals from the genus *Arctocephalus*: the South American fur seal, the Antarctic fur seal, and the sub-Antarctic fur seal. These species were chosen because there are occurrence records of these three species on the coast of RS (Fig. 1).

Image database and pre-processing

The first step was the creation of a database with 121 images from reliable sources, such as websites from pinniped specialists (pinipedesdosul.com.br; http://r3animal.org/; observation.org; ecoregistros.org; https://ciclovivo.com.br/; https://isnportal.com.br/; superstock.com; inaturalist.org; https://www.alamy.com; cma.sarem.org.ar; sealifebase.ca; iucnredlist.org); the scientific literature (Vigário, 2010; Jefferson et al., 2015; Cárdenas-Alayza, 2018); and photos taken by members of the Mammal Ecology Laboratory at the Universidade do Vale do Rio dos Sinos (UNISINOS) and Grupo de Estudos de Mamíferos Aquáticos do Rio Grande do Sul (GEMARS). This image database contained only photos of adult males, which have more visible and definitive diagnostic characteristics compared to females and juveniles, the latter of which are still undergoing developmental changes, making classification more challenging. The selection of images of adult males is justified by the ability to train with more distinct examples, enabling the generation of specific weights with high accuracy for pinnipeds. These weights can then be applied in the training of new sets of images, encompassing males, females, adults, juveniles, and even pups. The face of each analysed specimen was selected in each image, including only the facial image. Afterwards, each image file was saved in JPG format with its species name (Fig. 2A, B, and C).

The images were randomized and split on average 70% for training (26 images of South American fur seals, 30 of sub-Antarctic fur seals, and 29 of Antarctic fur seals) and 30% for testing (12 images of each species) (Fig. 2D). Since the images were of different resolutions (sizes), they were all reshaped to 100 x 100 pixels for standardization (Fig. 2E) and kept with three RGB colour channels (Red, Green, and Blue). Each image for training and testing was assigned a "class" value corresponding to the species in the image: 0 (zero) for South American fur seal, 1 for sub-Antarctic fur seal, and 2 for Antarctic fur seal. Each "class" consisted of the response value associated with the features (values and patterns of pixels) of each image and also the values of the output layer of the ANN (part of the classification). At this stage, the probability value assigned to each class determines which species the image corresponds to. Before generating the CNN, the class values were transformed into categorical values. The pixel values of the images were normalized between 0 and 1 (Fig. 2E). Each species was represented by different categorical values: label 0 = South American fur seal, label 1 = sub-Antarctic fur seal, and label 2 = Antarctic fur seal. Moreover, normalization is necessary because the pixels have a large distance between their values (between 0 and 255). Since the maximum value for colour presence is 255, all pixel values were divided by 255 (Chollet, 2018).

The general structure of a CNN consists of two parts: convolutional filters or layers (Convolutional2D and MaxPooling2D) for extracting parameters (pixel values and patterns) from each image (Fig. 2F and G), and a classification layer (ANN) (Fig. 2I). Convolutional2D applies a set of filters (also called kernels) to the input image through a convolution operation. Each filter is a small matrix that traverses the original image in small steps, multiplying the values of corresponding pixels and summing them to produce a value in a new matrix called feature maps. MaxPooling2D reduces the dimensions of the data while retaining the most important features extracted by the Convolutional2D layer. It divides the feature map into small regions (*e.g.*, 2 x 2 or 3 x 3) and, for each region, keeps only the maximum value (Haykin, 2009; Chollet, 2018).

The classification layer (Fig. 2I) is an ANN that receives the parameter values extracted by the Convolutional2D and MaxPooling2D layers (Fig. 2F and 2G). ANNs take the input features and multiply them by weights, and the result is used as input for the next (hidden) layer. The weights are recalculated to improve the operation of the network. Finally, an activation function returns a probability value for the output layer. The highest probability value corresponds to the identified class (species) in the image (Fig. 2I) (Chollet, 2018).

Parameter extraction step ("features")

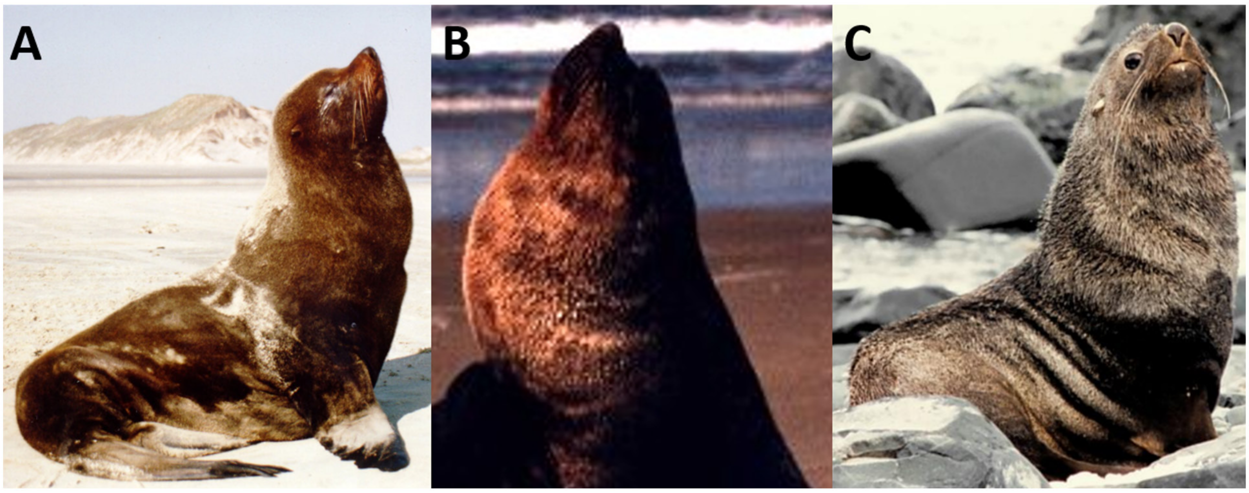

Figure 1. Species of *Arctocephalus* analysed in this study. (A) a South American fur seal *Arctocephalus australis* in southern Brazilian coast, photo: Márcio Borges-Martins, (B) a sub-Antarctic fur seal *Arctocephalus tropicalis* in southern Brazilian coast, photo: Larissa R. de Oliveira, and (C) an Antarctic fur seal *Arctocephalus gazella* in Deception Island, Antarctica, photo: Luciano Dalla Rosa.

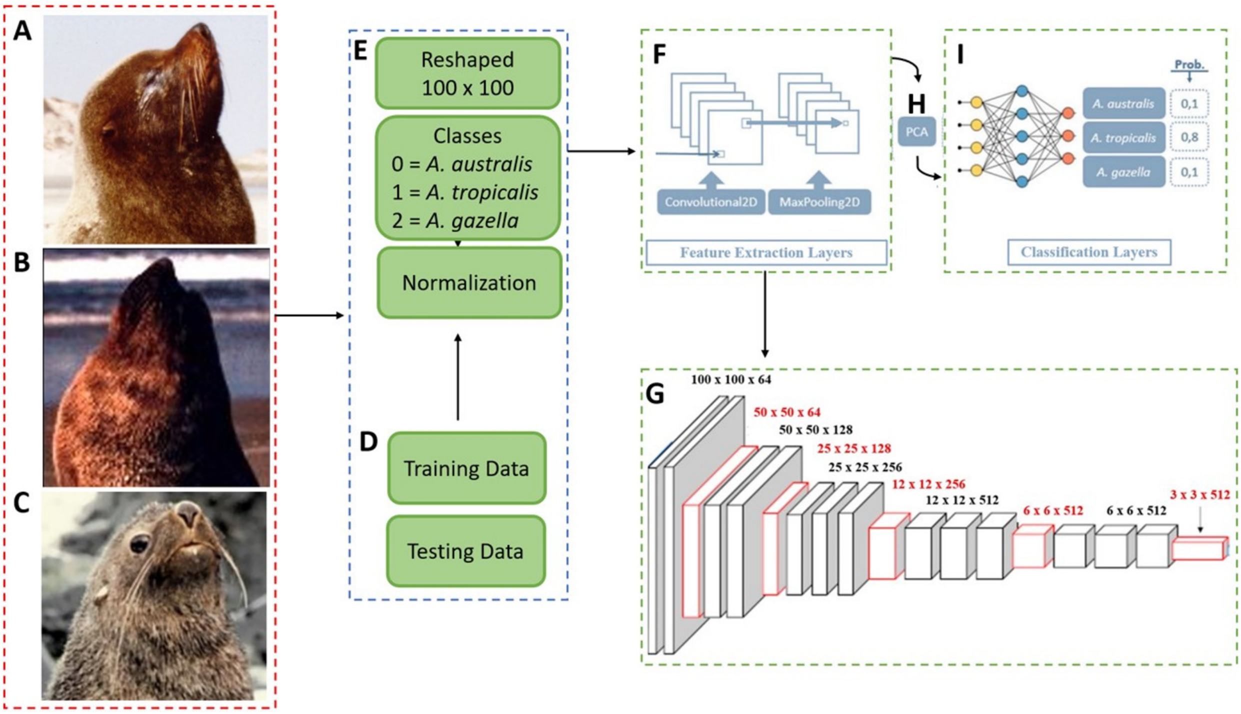

Figure 2. Overview of the development and implementation of the convolutional neural network (CNN) model to classify/identify three species of southern fur seals found in the southern Brazilian coast from facial images. Red dashed line: images with the facial region cropped from (A) a South American fur seal *Arctocephalus australis* in southern Brazilian coast, photo: Márcio Borges-Martins, (B) a sub-Antarctic fur seal *Arctocephalus tropicalis* in southern Brazilian coast, photo: Larissa R. de Oliveira, and (C) an Antarctic fur seal *Arctocephalus gazella* in Deception Island, Antarctica, photo: Luciano Dalla Rosa. Blue dashed line: preprocessing of the cropped images, where (D) separation of the images into training and test data. (E) Reshaped to 100 x 100 pixels resolution, separation of the species into classes and normalization of pixel values. Green dashed line: architecture of the convolutional neural network model, where (F) corresponds to a simplified scheme of the convolutional layers showing the Convolutional2D and MaxPooling2D feature extraction layers. (G) Corresponds to the VGG16 architecture with its Convolutional2D layers (in red) and MaxPooling2D layers (in black), the sizes of activation maps, and the number of convolutional filters for each layer. (I) Simplified scheme of an Artificial Neural Network (ANN) with its input layers (yellow circles), hidden layers (blue circles), and output layers (orange circles). (H) Corresponds to the dimensionality reduction process, achieved through the application of Principal Component Analysis (PCA). Source: Adapted from Adit Deshpande (https://adeshpande3.github.io/) and Choi et al. (2021).

We used the code called "Python for Microscopists" (Bhattiprolu, 2020), available on the GitHub platform (https://github.com/), as the basis for our analysis. This code explains the process of using pre-trained VGG16 (Fig. 2G) model weights as feature extractors for neural networks and machine learning, and the use of dimensionality reduction of images through principal component analysis (PCA) to reduce the number of features for faster training and better model development (Fig. 2H) (Bhattiprolu, 2020).

In VGG16, each image was passed through a set of five blocks (Fig. 2G). The first and second blocks consisted of two Convolutional2D layers (Conv1 and Conv2) with a filter size of 3 x 3 each, followed by a "relu" activation function. Each of the Convolutional2D layers in block 1 had 64 convolutional filters, while in block 2 each had 128 convolutional filters. The convolution stride was fixed at one pixel. This configuration preserves spatial resolution, and the size of the output activation map was the same as the input image dimensions. The activation maps were then passed through a 2 x 2 window MaxPooling2D layer, with a stride of two pixels. This halves the size of the activations. Thus, the size of the activations at the end of the first block was 50 x 50 x 64, and 25 x 25 x 128 at the end of the second block. Blocks 3, 4, and 5 were composed of three Convolutional2D layers (Conv1, Conv2, and Conv3 each) with a filter size of 3 x 3, followed by a "relu" activation function. Each of the Convolutional2D layers in blocks 3, 4, and 5 contains 256, 512, and 512 convolutional filters, respectively. The remaining MaxPooling2D layers were also 2 x 2 windows, with a convolution stride of two pixels. At the end of the five blocks, the size of the activations was 3 x 3 x 512 (Fig. 2G) (Simonyan & Zisserman, 2014).

Due to the large number of parameters extracted from the images, a dimensionality reduction process was performed in the first stage through PCA (Fig. 2H). These output parameters from the parameter extraction stage were then fed into the input layers of the next stage of the ANN model, the classification stage. According to Hair et al. (2009), PCA is a statistical approach that can be used to analyse interrelationships among a large number of variables with the aim of finding a way to translate the information contained in a number of original variables into a smaller set of variables with minimal loss of information. PCA reduces input data redundancy, eliminates potential correlations, and extracts the most relevant feature vectors for the change in data direction, while improving classification results (Ren et al., 2016). Different numbers of principal components were tested for PCA, but the value that provided the best results was 67 components.

Classification step - ANN

After performing the above steps, an ANN with three layers (Fig. 2I) was built, namely: A - an input layer with 67 components (PCA); B - a hidden layer with 256 neurons and *relu* activation function; and C - an output layer with three classifications (one for each species) and *softmax* activation function. The *relu* activation function introduces a non-linear value to the model through calculation. The *softmax* activation function returns the probabilities of the multiclass classification, *i.e.*, the probability of the analyzed image being species *A. australis*, *A. tropicalis*, or *A. gazella*. All layers were densely connected (Fig. 2I).

To adjust model weights, we used the "RMSprop" optimizer with a learning rate of 0.001. To analyse model performance, we used the "categorical crossentropy" loss function, accuracy, and a confusion matrix. The model was trained for 150 epochs. All analyses were performed using Python in Google Collaboratory or Google Colab (Bisong, 2019).

Results

The analysis of the 121 images and the applied layers of VGG16 allowed for the extraction of a total of 14,714,688 parameters in the model (Supplementary Material 1). The PCA reduced the model to 18,179 parameters (Supplementary Material 2), resulting in a significant improvement in the parameter's reading time and model accuracy.

After the training was completed, the model was submitted to the selected test images (12 from each species). The model correctly attributed 30 out of 36 images, classifying them correctly according to the previously informed species. Therefore, the accuracy of the model was 0.8334, meaning 83.34% of correct classification in the test images.

Of the 12 images of South American fur seals (label 0), the model correctly attributed 10, while the other two were incorrectly classified as Antarctic fur seals. Of the 12 images of sub-Antarctic fur seals (label 1), the model also correctly attributed 10, while the remaining two were incorrectly classified as a South American fur seal and an Antarctic fur seal. Of the 12 Antarctic fur seal images (label 2), the model again correctly classified 10 but misclassified one as a South American fur seal and another as a sub-Antarctic fur seal (Fig. 3). It is important to emphasize that these labels were provided by training and testing conducted by ANN and CNN algorithms that learn to associate labels with examples. This results in labelled values or predicted categories, which are in this case three specific fur seals species.

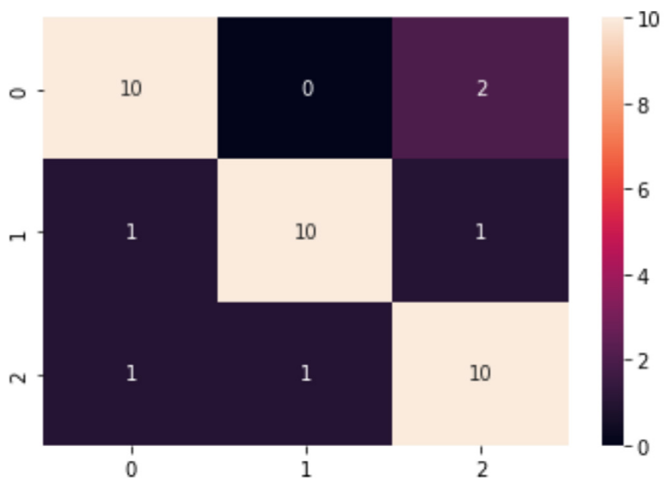

Figure 3. Confusion matrix with the result of the image classification analysis of three species of fur seals of the genus *Arctocephalus*. On the y-axis are the actual labels (0 = *Arctocephalus australis*; 1 = *Arctocephalus tropicalis*; and 2 = *Arctocephalus gazella*) On the x-axis are the predicted labels, *i.e.,* the labels that the model identified. Numbers from 0 to 10 in the matrix correspond to the number of classified images.

Discussion

The main goal of this study was to propose the use of an AI method based on CNN and ANN to classify/identify three species of fur seals found on the south coast of Brazil . Our results suggest that the generated model is capable of classifying facial images of the three species with high accuracy (83.34%).

The results of our model classifications of fur seal images can be considered good in comparison with other similar studies with seals that used artificial intelligence, and models with pre-trained weights (VGG16). To identify Saimaa ringed seal (*Pusa hispida saimensis*) individuals based on external morphological characteristics, Chehrsimin et al. (2017) analyzed 194 seal images and achieved an accuracy of 44% using the HotSpotter image identification algorithm, while the Wild-ID algorithm achieved only 13% correct identification of individuals in the images. These algorithms use patterns of spots, stripes, and markings on the bodies of species such as zebras, giraffes, and leopards to identify the individuals in the images (Chersimin et al., 2017). Speed et al. (2007) assessed the reliability of using the Interactive Individual Identification System (I³S) platform to identify individual specimens from photos based on natural markings. Through the analysis, the application correctly attributed 93 out of 100 images of whale sharks. These studies highlight the importance of identification methods where, simply by including an image in the platform, it is possible to correctly identify the individual in question without the need for more invasive methods, making it an easily accessible and rapid tool for everyone.

Using a transfer learning approach similar to our study, Loos & Ernst (2013) conducted an individual identification study of chimpanzees by adapting human facial detection and recognition technology. Analysing 6,522 processed images of 95 chimpanzees from zoos and the wild, the authors of the study achieved 96.48% and 82.27% correct classifications, respectively. These high accuracy values are possibly attributed to the use of pre-trained weights from a human facial recognition model, as they are a major focus of research, and humans and chimpanzees share significant similarities.

Molecular markers play crucial role in the field of systematics, providing valuable evidence for species identification as well as understanding evolutionary relationships among organisms (Avise, 1989). In this context, an attribution and classification study of southern fur seal species used nuclear genes extracted from genotypes from seven microsatellite loci and was able to correctly attribute 100% of Antarctic fur seal specimens and 93.4% of South American fur seal specimens (Oliveira et al., 2008), obviously taking into account that they are completely different markers, and both studies have different sample sizes. However, this comparative study with nuclear markers is the only genetic study available directly related to the identification of two of the three fur seal species analyzed here. The comparison of these values to those obtained by the machine learning-based model using external morphology images of the three fur seals species suggests that the neural network offers a good alternative for classification, as it also has a good attribution capability.

A possible reason for the classification errors observed in this study is that the machine learning models could not visually identify the same patterns that humans found. For example, one of the images was incorrectly identified as an Antarctic fur seal but the individual had clear diagnostic characters of sub-Antarctic fur seal (King, 1983), the chest and face with much lighter fur than the rest of the body. In another incorrectly attributed image, the specimen was an Antarctic fur seal, and the confusion in identifying it as a South American fur seal likely stemmed from the individual in the image being brown and appearing wet. Another image incorrectly was confused with the sub-Antarctic fur seal, possibly because the guard hairs (*i.e.*, under the outer hairs) were lighter and appeared more visible from the angle in the photo. Interestingly, these two species were once considered a single species divided into two subspecies: *A. gazella gazella* and *A. tropicalis gazella* (King, 1983). They are now considered distinct species, mainly due to major differences in their dentition (Repenning et al., 1971).

In this study, we presented a methodology that uses artificial intelligence to recognize images of southern fur seals of the *Arctocephalus* genus in order to classify and identify the three most frequent species along the Brazilian coast and RS. The database and artificial intelligence model generated in this study could be associated in the future with a citizen science tool through a cell phone application being developed to identify the main pinniped species that occur on the Brazilian coast. This tool could bring society closer to the studies on pinniped occurrence patterns in Brazil, because it combines easy use (only requiring the submission of a photo). Thus, coastal residents can assist in the detection of new records of the eight species confirmed for the coast of Brazil (Pinedo, 1990; Oliveira, 2013; Frainer et al., 2018).

Annually, these occurrences have been associated with their post-reproductive foraging trips from their breeding colonies, partially driven by their movements by ocean currents (Pinedo, 1990; Simões-Lopes et al., 1995; Oliveira et al., 2006). However, the detection of some species such as the Antarctic and sub-Antarctic fur seals based on photos outside their usual distribution areas may suggest that climate change is already affecting their dispersal routes and foraging zones (Oliveira, 1999; Ferreira et al., 2008; Sousa-Lima et al., 2022; Oliveira et al., 2024). In a study published by Sousa-Lima et al. (2022), an individual of sub-Antarctic fur seal was sighted in the São Pedro and São Paulo Archipelago, outside its usual distribution range. The individual was spotted by Brazilian Navy staff, who took photos of the animal and sent them to experts for species identification. Actions like this are extremely important, as they combine citizen science and bring highly relevant information to researchers in the field.

This is the first study to employ artificial intelligence to distinguish *Arctocephalus* species by their external morphology. The use of this methodology in other taxa and its application to the identification of fur seals can also assist researchers and interested citizens in the visual identification of these species in the field, whether in reproductive or non-reproductive areas.

One of the biggest challenges for machine learning is the demand for a large training dataset with sufficient quality to achieve good accuracy (Beyan & Browman, 2020; Malde et al., 2020). While high-quality images may enhance the training of

CNN models, it is crucial for these models to demonstrate the ability to generalize to make accurate predictions across various real-world scenarios, regardless of image quality. In this context, it is important to mention the use of "transfer learning" technique in this study, as it allows models to benefit from pre-trained weights without requiring the time and budgetary capacity they usually demand (Kurz, 2020). By using a previously developed code for image classification, it was possible to achieve better results in less time (Goodwin et al., 2022).

With the pre-trained weights for these three species of the genus *Arctocephalus*, we plan to expand the model training in the future by incorporating new images of males of five *Arctocephalus* species not assessed in this study: New Zealand fur seal (*A. forsteri*), Galapagos fur seal (*A. galapagoensis*), Juan Fernandez fur seal (*A. philippii*), Cape fur seal (*A. pusillus pusillus*), Australian fur seal (*A. pusillus doriferus*), and Guadalupe fur seal.

Studying morphologically similar species is a challenge because their differentiation is difficult, often time-consuming, and requires the combined use of other methods, such as molecular techniques for identifying cryptic species, and validation by experts. Finding alternative methods that assist in the effectiveness of species identification, not only by scientists but by all citizens, is not only scientifically relevant but also a way to bridge the gap between society and conservation science.

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