Brazilian Birds of Prey - A New Dataset and Classification with Deep Neural Networks

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***Abstract*—Birds of prey play an essential role in maintaining the health of their ecosystems. In Brazil, where there is a vast amount of biodiversity, the identification and monitoring of predatory birds are essential for maintaining the ecosystem. However, developing computational methods for the classification of predatory birds based on images is not trivial, given the many possible variations, such as angles, lighting, birds camouflage, and others. Nowadays, Transfer Learning (TL) approaches have gained popularity for many applications due to a large amount of knowledge previously acquired by models from huge datasets, which can be leveraged for other similar problems. In this paper, we present a dataset of birds of prey images and also introduce a baseline classification benchmark using the TL approach. The experiments were divided into two subcategories: families and species classification. The proposed dataset contains 42,475 samples, from 6 families and 41 species. The samples of the dataset contain birds in different positions and angles, with great variety with respect to background and illumination. Baseline results achieved an F1-Score of 92% in family and 80% in species classification.**

***Keywords*—Fine-Grained Classification; Convolutional Neural Network; Machine Learning.**

I. Introduction

Observation of birds in their ecosystem can lead to a better understanding of their behavior and lead to important biological discoveries, such as hawks nesting and eating habits [1], [2]. In Brazil, the plurality of bird species is immense because of its large territorial extension. Only in the Pantanal region, over 400 birds species were registered [3]. For the observation of species, minimum human interference is crucial to not cause behavioral alterations. It would be interesting to have an automatic detection and classification system to help researchers study those birds in their natural habitat.

Despite the great importance of predatory birds in the Brazilian ecosystem, to the best of our knowledge, there is no work in the recent literature that classifies images of those birds.

In fact, the bird classification problem using image samples is a challenging task. Since nature is not a controlled environment, many issues arise. For instance, birds of the same species may be different according to their age, development stage, or environmental factors, which affects their form, color, and size. Other issues are partial occlusion by objects, images obtained from large distances, and also subjects performing different activities (i.e., flying or eating). Bird camouflage and light conditions could also hinder the image classification performance. When species classification (fine-grained) is considered, the problem becomes even harder, given that slight nuances may be the only difference between distinct species from the same family. For these reasons, developing a robust Computer Vision (CV) approach to this problem is still a challenge.

CV allied to Computational Intelligence is suitable to accomplish this kind of classification task. One of the most successful areas of Computational Intelligence is Deep Learning (DL), which has reached the state-of-the-art in several CV problems [4]. Unlike traditional approaches, DL provides an end-to-end learning system, learning to extract features and also classify samples into categories.

With the popularization of DL methods, several models have been presented and made available in the literature. In this regard, theses pre-trained models have been used to accomplished other similar tasks using the Transfer Learning technique. Among such models, Inception-v3 is one of the most popular due to its high performance in the 1000-class classification challenge [5]. This network has been trained using the ImageNet dataset with over 14 million samples. Due to its outstanding performance, it has been frequently used as a base model for other CV problems.

In this work we introduce the Brazilian Birds of Prey image dataset. In addition, we present a baseline performance using DL models with a Transfer Learning approach, and an evaluation protocol in two settings: classification per family and per species.

This article is structured as follows. Section II reviews some related works. Section III presents the theoretical aspects of Computer Vision and Image Classification. In the sequence, Section IV shows the dataset described in this work. The methods and the model used for birds classification are shown in Section V. Results and their analysis are presented in Section VI. Finally, Section VII shows the conclusions and future works.

II. Related works

Many works in birds classification try to categorize birds by sound. For instance, [6] classifies birds by comparing the spectrogram signals generated from audio. Other works recognize species in audio recordings using CNNs [7] and Convex Spectral Embeddings [8].

In classification using images, [9] uses computer vision techniques that include segmentation and a feature set of appearance and motion. From the same author, [10] improves the results using the features allied with classifiers, being able to achieve 90% correct classification in their bird's flight dataset.

Using transfer learning and multi-stage training, [11] classifies birds by species in the CVIP 2018 Challenge, achieving an F1-score of 55.67%. Other works in the bird classification problem are based on color features [12], two-level features [13], among others found in the literature.

Various datasets for fine-grained classification also exist, like the classification of dog breeds [14], the Caltech-UCSD Birds, containing 200 birds species for classification [15], and the aircraft visual classification dataset spanning 100 aircraft models [16], among others that deal with diverse classes.

Our work provides a transfer learning approach using our own set of data. This dataset provides us with a birds classification problem by separating them in families and species, the dataset is fine-grained and we also provide a solution in classification by using Inception-v3.

The dataset we provide differs from others by having only birds that were sighted in Brazil. Moreover, it contains only predatory birds, which are at diverse stages of development, diverse environments, and performing different activities. Our dataset also has unbalanced classes making the recognition task more challenging.

III. Computer Vision and object classification

Computer vision is a research area that aims to make the computer assign semantic meaning to an image or video. It is a large area that includes computer science, mathematics, biology, psychology, among many others. The joint effort of these areas has led to a wide range of different methods for detection and classification of images and videos.

A. Convolutional Neural Network

The Convolutional Neural Network (CNN) [17] is a class of feed-forward neural network that has wide use in digital image processing and pattern analysis problems. The outstanding advantage of a CNN is that it does not require much preprocessing when compared to traditional machine learning algorithms. This is due to the fact that CNNs automatically learn a feature extractor that aims at maximizing performance. This process produces a feature extractor that is fine-tuned for the data, which would need to be implemented manually otherwise. An example of a classic CNN LeNet5 architecture for image classification is shown in Figure 1 where an input is transformed through convolutions and pooling layers until a result is returned in the output.

Transfer Learning (TL) is the approach in which knowledge learned in a given task is transferred to other (somewhat related) task [18]. TL in computer vision is the process of using a CNN model trained in a given domain for extracting features of images of other (related) domain, which are later classified by another method. In this work, TL was used as the starting point to train the last layers of a CNN. The basic idea of TL is represented in Figure 2, where the model and weights are imported, replacing only the last fully connected and softmax layers.

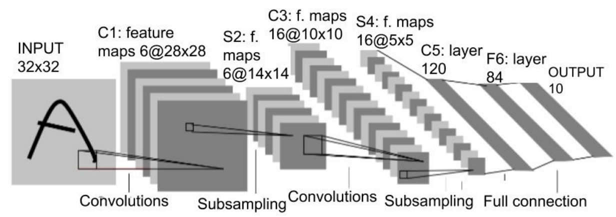

Figure 1. Architecture of the LeNet5 CNN [17].

IV. Dataset

Due to our interest in collecting images of birds that were found in Brazil, the images were obtained at the wikiaves website[1]. This website contains information about all birds presented in Brazilian fauna while promoting the observation of birds. In the website, by searching the bird species name, we can find all relevant information about the bird, such as their scientific classification and habits, like reproduction and feeding.

The birds presented in this work are all encountered in Brazil to some extent. We find them in diverse biomes like the Brazilian Cerrado and Caatinga, with birds such as the *Cathartes aura* and the *Elanus leucurus* [20], also found in other parts of the world. This dataset also contains birds that exist mostly in Brazil, like the *Megascops sanctaecatarinae* that exists only in southern Brazil, mostly in *Santa Catarina*.

Another characteristic of these birds is that all of them are predators and in many images are seen capturing or eating prey. The birds from each species presented in this work can be seen in Figure 3.

What makes this dataset a difficulty, is the fine-grained classification problem, which aims to differentiate between various categories within an input category. Here, we also do not know in which state the object will be in the image. It can be with occlusion, at a great distance, with over one object per image and various other states that can happen when taking a picture. With birds, the images span through various stages of their lives and include them performing several actions, such as flying or eating, along with usual image noise.

V. Methodology

An overview of our method can be seen in Figure 4, showing the processes from the image acquisition (Webcrawler) to the DL model training and validation. Each step is explained in the following Sections.

[1] https://www.wikiaves.com.br/

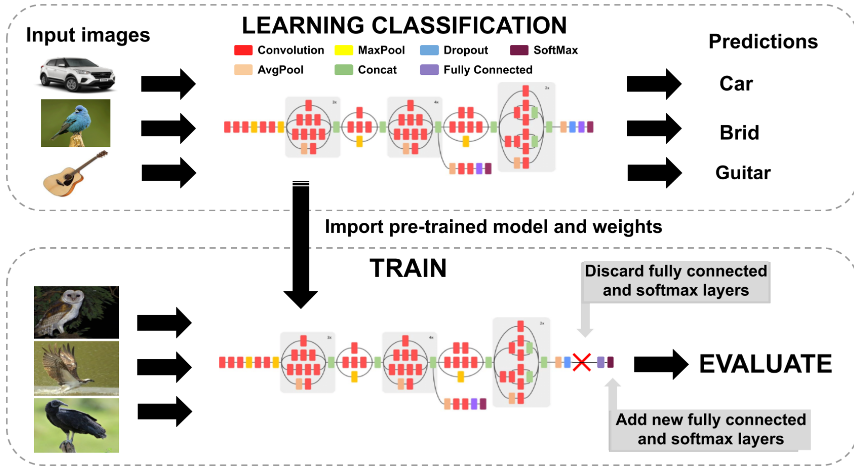

Figure 2. Basic representation of the Transfer Learning method. Adapted from [19].

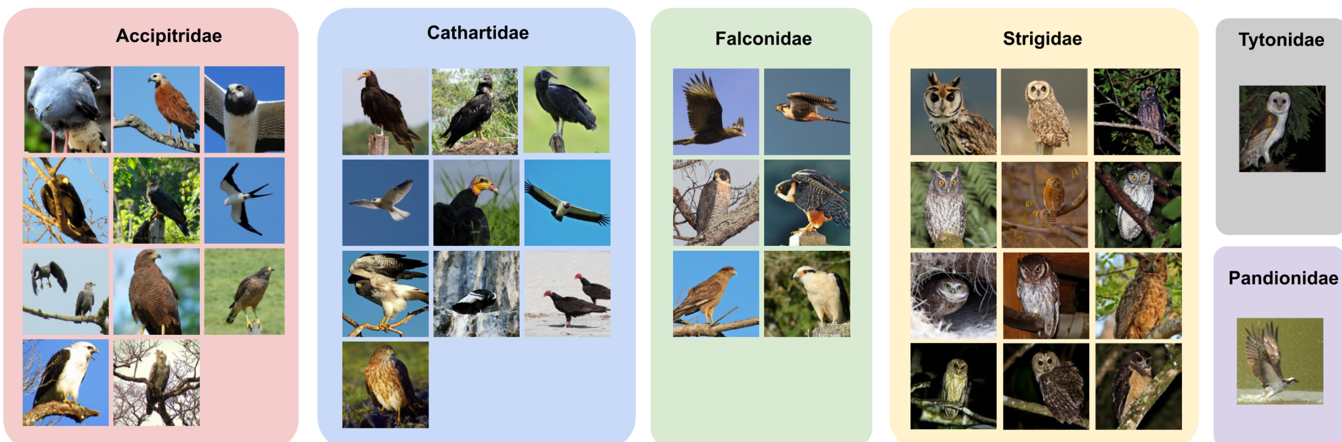

Figure 3. Example of all classes of birds families

A. *Transfer Learning*

Transfer Learning is the process of using previously acquired knowledge in a problem and applying it to a different, but similar one [21].

In neural networks the transfer is made by allocating weights and layers, changing the inputs and outputs of the network, along with some layers that may be unnecessary for the problem. This process is seen detailed in Figure 2, showing the transfer learning adapted to our problem using the Inceptio-v3 architecture as base.

B. *Webcrawler*

For the building of the dataset, we downloaded the images using semi-manual web scrapping by searching a specific bird name in the wikiaves website, and getting the pictures presented in the gallery of each bird, containing all registers found by its users in the Brazilian landscape. The tool used for this was the data miner[2], an extension for Google Chrome that helps in extracting data from websites.

[2]https://data-miner.io/

Table I shows the number of samples in the dataset divided by species and families. As it can be seen, the dataset is unbalanced containing classes with more samples than the others.

In the division of species shown in Table I the classes represented are more balanced than in the family classification, however the unbalance continues as shown by the *Vultur gryphus*, that contains fewer samples than the other classes.

We distributed the number of samples into 29,731 for the train set and 12,743 for testing. These images are divided into six classes for the family classification problem and 41 classes for species classification. All images were resized to 310x310 pixels when divided into their respective classes.

The dataset contains noise in some of its images, where the bird present can not be identified even by human eyes. Also, by being a fine-grained dataset, its images are difficult to classify, needing an expert in the area to correctly address the birds in the pictures.

There are also images containing birds of various stages of development, from birth to adulthood, making the dataset more challenging to correctly classify those pictures.

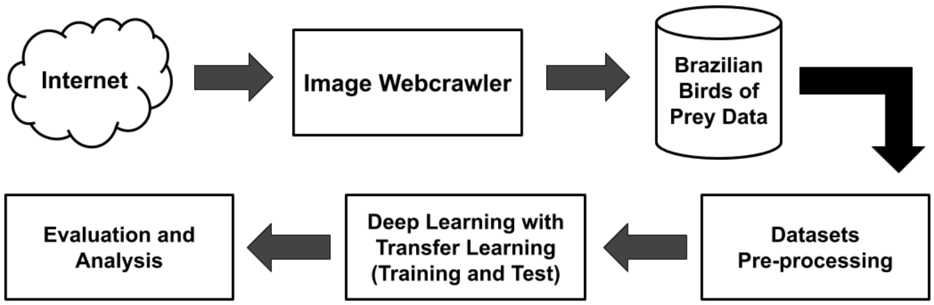

Figure 4. Overview of the proposed process.

This dataset may also work for hierarchical classification since, in biology, species are all represented in a genus that is contained within a family. We can see this representation in Table I which contains the birds found in this work, classified by family, genus, and species.

The dataset is available for download in the Bioinformatics and Computacional Intelligence Laboratory (LABIC) website[3].

C. Pre-processing

As presented in Section IV the dataset was built first by downloading, then separating the images, dividing each bird in their proper family and species classification and labeling them.

As input for the model, all images were converted to the Inception-v3 requirements, which is to the 224x224 size and normalized between -1 and 1. We also used the RGB (Red, Green, Blue) color space for the experiments.

D. Deep Learning Model and Evaluation Metrics

We build the base model using the Inception-v3 provided by Keras[4]. The model consists of a feature learning part with convolutional layers and a classification part with fully-connected and softmax layers.

After building the base model, we discard the fully-connected and softmax layers and add an Average Pooling and a fully-connected layer with softmax activation containing the number of classes needed for the respective problems (6 for families and 41 for species), as shown in Figure 2.

For the training of both problems we split the data into training and validation, being 25% destined to validate the model and 75% for training.

The optimizer chosen was the Stochastic Gradient Descent (SGD) [22] with a learning rate of 0.0005 and batch size of 128.

This training model was then compiled using the categorical cross entropy loss [23], where only one result is considered correct, and using macro F1-score as metrics. Since the classes were unbalanced in both problems, the use of macro F1-score is recommended, since it takes in account the precision and recall making the statistical evaluation more accurate [24].

[3]https://labic.utfpr.edu.br/

[4]https://keras.io/

TABLE I
BIRDS IN THIS WORK SEPARATED BY FAMILY, GENUS AND SPECIES.

Family	Genus	Species	Samples
Accipitridae	*Accipiter*	*striatus*	840
	Busarellus	*nigricollis*	1,160
	Buteo	*albonotatus*	929
	Chondrohierax	*uncinatus*	1,120
	Circus	*buffoni*	840
	Elanoides	*forficatus*	1,140
	Elanus	*leucurus*	1,081
	Geranoaetus	*albicaudatus*	880
		melanoleucus	1,000
	Geranospiza	*caerulescens*	1,000
	Harpia	*harpyja*	954
	Heterospizias	*meridionalis*	1,040
	Pseudastur	*polionotus*	740
	Rupornis	*magnirostris*	960
	Urubitinga	*coronata*	1,100
			14,784
Cathartidae	*Cathartes*	*aura*	1121
		burrovianus	1,120
		melambrotus	876
	Coragyps	*atratus*	1,221
	Sarcoramphus	*papa*	1,174
	Vultur	*gryphus*	214
			5,726
Falconidae	*Caracara*	*plancus*	1,180
	Falco	*femoralis*	1,100
		peregrinus	1,130
		rufigularis	1,140
	Milvago	*chimachima*	1,140
		chimango	1,120
			6,810
Pandionidae	*Pandion*	*haliaetus*	1,260
Strigidae	*Asio*	*clamator*	1,120
		flammeus	1,140
		stygius	1,120
	Athene	*cunicularia*	1,140
	Bubo	*virginianus*	1,120
	Glaucidium	*brasilianum*	1,140
	Megascops	*atricapilla*	625
		choliba	1,120
		sanctaecatarinae	1,274
	Pulsatrix	*koeniswaldiana*	1,120
	Strix	*hylophila*	1,120
		virgata	736
			13,895
Tytonidae	*Tyto*	*alba*	1,120
Total			42,475

The F1-Score is the harmonic mean of precision and recall, in our case we used the macro calculation of the F1-Score, using the total number of classes C to estimate the precision and recall.

The equations are below where TP equals true positives, FP means false positives and FN is false negatives.

Macro averaged precision:

$$P = \frac{1}{C}\sum_{i=1}^{C}\frac{TP_i}{TP_i + FP_i}. \quad (1)$$

Macro averaged recall or sensitivity:

$$R = \frac{1}{C}\sum_{i=1}^{C}\frac{TP_i}{TP_i + FN_i}. \quad (2)$$

Macro F1-score:

$$F1 = 2 \times \frac{P \times R}{P + R}. \quad (3)$$

In both problems the parameters used for the classification tasks were the same, being the only difference the number of classes between both problems.

In this work, we used a computer with the IntelCore-i7 8700 processor, 32 GBytes of RAM and an Nvidia Titan Xp GPU. The Keras library using the TensorFlow backend was used to train and test the model.

Finally, after the models were trained, they were tested in their respective problems resulting in the values seen in Tables II and III, which are going to be explained in the following section.

VI. Analysis and Results

The experiments were divided into family and species classification. In family there were 6 classes to classify, while in species there were 41.

A. Family Classification

In family classification, the objective was to classify each of the Brazilian birds of prey families.

Table II shows the results per class obtained in the classification per family, it demonstrates that the *Pandionidae* class has the lowest F1-score caused by the low recall, which means that most images are misclassified as another family. This can be related to the fact that it is one of the two classes with the lowest samples in family recognition, while also being similar to other types of birds. This does not occur with the *Tytonidae* class, the other class with fewer samples , which can be explained by the different traits of the *Tyto alba* owl, which are very distinct when compared to other birds.

Figure 5 represents the confusion matrix of family classification, where some classes explained previously were classifies as others. For example, *Cathartidae* (class 1), *Falconidae* (class 2) and *Pandionidae* (class 3) were classified as *Accipitridae* (class 0). Figure 6 shows the similarity of these families, first and second columns are correct and wrong classification examples respectively, and the third column is an example of a positive class.

TABLE II
RESULTS OBTAINED IN SPECIES CLASSIFICATION.

Class	Name	Precision	Recall	F1-score
0	*Accipitridae*	0.90	0.93	0.92
1	*Cathartidae*	0.93	0.91	0.92
2	*Falconidae*	0.90	0.89	0.89
3	*Pandionidae*	0.90	0.80	0.85
4	*Strigidae*	0.98	0.98	0.98
5	*Tytonidae*	0.98	0.96	0.97
	macro avg	0.93	0.91	0.92

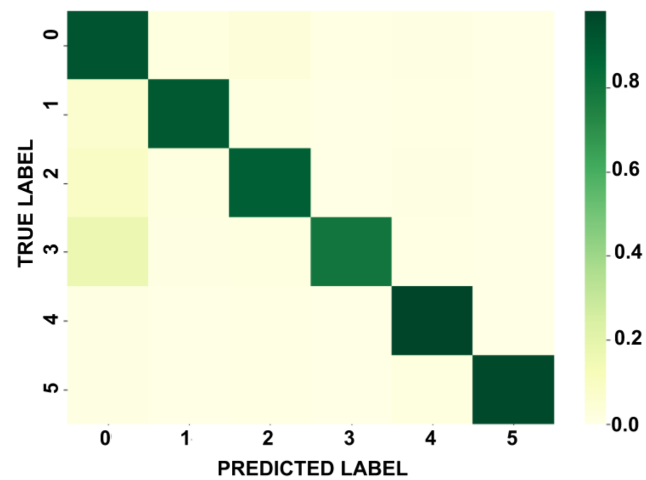

Figure 5. Confusion matrix for 6 bird families classification

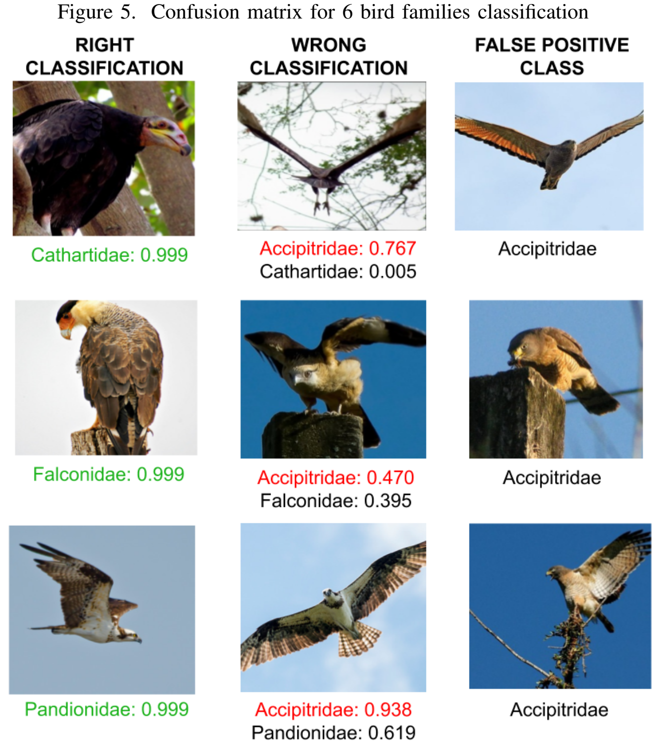

Figure 6. Family classification examples: Left column represents correct classifications and their probability; middle column represents classification errors, in red the false positive probability and below it, the true class probability; right column represents the false positive class of each row.

B. Species Classification

In species classification, the experiment was aimed at correctly classifying 41 Brazilian birds of prey species.

TABLE III
RESULTS OBTAINED IN SPECIES CLASSIFICATION

Class	Name	Precision	Recall	F1-Score
0	*Glaucidium brasilianum*	0.98	0.97	0.98
1	*Caracara plancus*	0.84	0.89	0.86
2	*Milvago chimachima*	0.80	0.84	0.82
3	*Falco rufigularis*	0.92	0.89	0.90
4	*Milvago chimango*	0.85	0.86	0.86
5	*Vultur gryphus*	0.24	0.22	0.23
6	*Athene cunicularia*	0.96	0.91	0.93
7	*Strix virgata*	0.88	0.96	0.92
8	*Strix hylophila*	0.97	0.95	0.96
9	*Asio clamator*	0.91	0.97	0.94
10	*Megascops choliba*	0.79	0.91	0.85
11	*Megascops sanctaecatarinae*	0.58	0.41	0.48
12	*Megascops atricapilla*	0.31	0.36	0.34
13	*Falco femoralis*	0.75	0.85	0.80
14	*Falco peregrinus*	0.90	0.78	0.84
15	*Busarellus nigricollis*	0.96	0.91	0.94
16	*Heterospizias meridionalis*	0.92	0.87	0.89
17	*Chondrohierax uncinatus*	0.77	0.75	0.76
18	*Rupornis magnirostris*	0.79	0.86	0.82
19	*Geranoaetus albicaudatus*	0.62	0.76	0.69
20	*Circus buffoni*	0.80	0.82	0.81
21	*Accipiter striatus*	0.70	0.72	0.71
22	*Elanus leucurus*	0.82	0.89	0.85
23	*Geranospiza caerulescens*	0.81	0.80	0.81
24	*Pseudastur polionotus*	0.80	0.80	0.80
25	*Harpia harpyja*	0.84	0.83	0.83
26	*Elanoides forficatus*	0.85	0.91	0.88
27	*Buteo albonotatus*	0.79	0.75	0.77
28	*Bubo virginianus*	0.91	0.94	0.93
29	*Asio stygius*	0.96	0.93	0.95
30	*Asio flammeus*	0.94	0.89	0.92
31	*Pulsatrix koeniswaldiana*	0.98	0.96	0.97
32	*Tyto alba*	0.95	0.97	0.96
33	*Cathartes melambrotus*	0.66	0.72	0.69
34	*Cathartes burrovianus*	0.74	0.74	0.74
35	*Coragyps atratus*	0.82	0.85	0.84
36	*Cathartes aura*	0.81	0.78	0.79
37	*Sarcoramphus papa*	0.77	0.75	0.76
38	*Urubitinga coronata*	0.79	0.62	0.69
39	*Pandion haliaetus*	0.81	0.83	0.82
40	*Geranoaetus melanoleucus*	0.73	0.66	0.70
	macro avg	0.81	0.81	0.80

Table III shows the values obtained by each species, the macro average of all species in this task is shown to be 80%, this score is worsened by the classes with lower f1-score, occurring in the *Vultur gryphus* (class 5),*Megascops atricapilla* (class 12), and *Megascops sanctaecatarinae* (class 11), those classes as seen in Figure 7, are being misclassified as other species.

Figure 8 presents the confusion matrix of species classification, showing that some classes were classified as others. For example, *Vultur gryphus* as *Sarcoramphus papa*(classes 5 and 37), *Megascops sanctaecatarinae* as *Megascops atricapilla* (classes 11 and 12), *Cathartes melambrotus* as *Cathartes burrovianus* (classes 33 and 34). Each pair of species that were confused belong to the same family (see Table I), indicating a higher similarity between theses species. Given these results, we performed using visual analysis of these miss classifications. The first and second columns in Figure 7 are correct and wrong classification examples respectively, and the third column is an example of a false positive class.

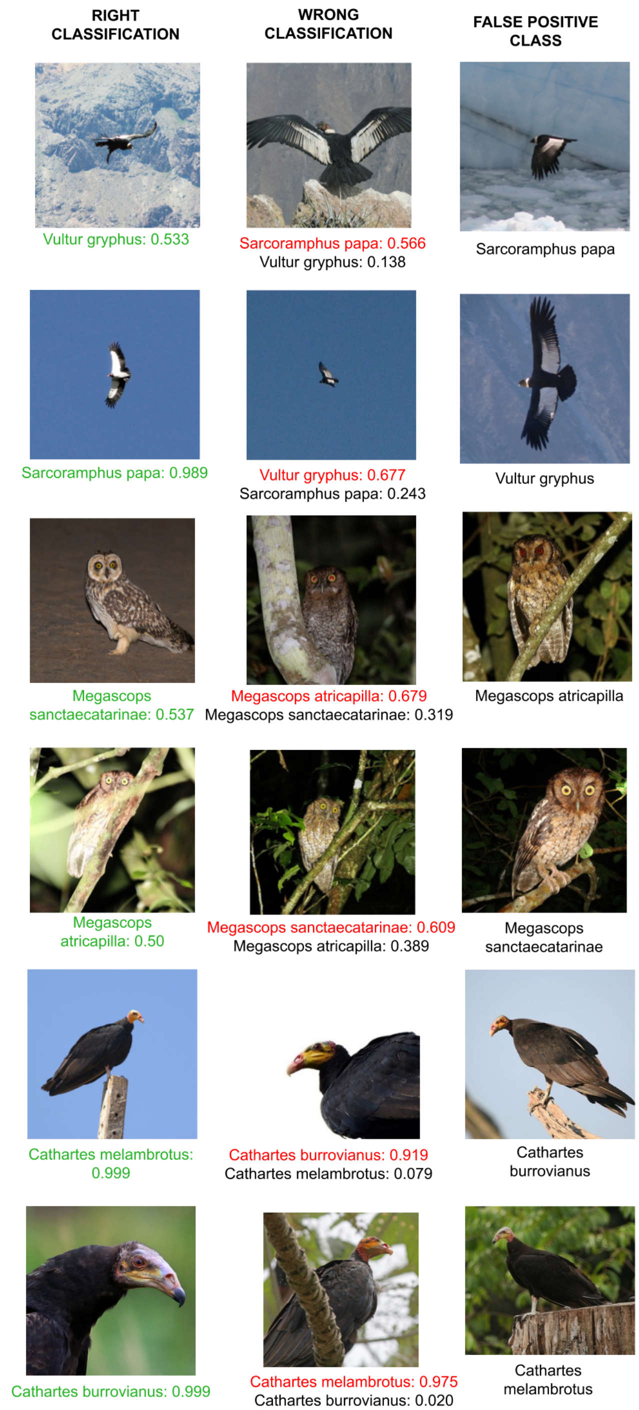

Figure 7. Species classification examples: Left column represents correct classifications and their probability; middle column represents classification errors, in red the false positive probability and below it, the true class probability; right column represents the false positive class of each row.

VII. CONCLUSION

In this work, we introduce a new dataset to classify Brazilian birds of prey into 6 families and 41 species in diverse situations. We also provide a benchmark solution for the birds classification problem using the Inception-v3 transfer learning

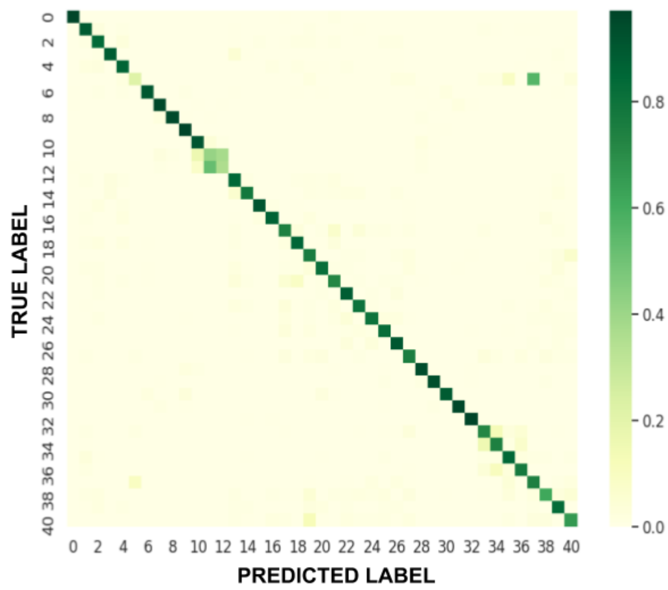

Figure 8. Confusion matrix for 41 bird species classification

approach.

This dataset presents a challenge in the fine-grained classification problem and by providing researchers with birds sighted in different Brazilian regions, we hope that this work helps the environmental preservation of those animals, and enhance the awareness and care to the Brazilian fauna.

Achieving a result of 80% F1-Score in the species and 92% in family classification (with some exceptions caused by visual appearances among some families and, especially species that belong to the same family), we demonstrate that it is possible for a CNN to classify the dataset. Providing this benchmark solution, we hope that other researchers may use it to train models in a fine-grained classification problem. This result also shows that there is still room for improvement in applying computer vision models to an unbalanced and fine-grained dataset.

As final conclusion, this work shows that fine-grained classification is still a relevant problem and, by providing a new dataset with a benchmark solution, we hope to increase research in the field while also showing the diversity of Brazilian fauna.

For future works, the dataset will be improved by decreasing noise and increasing the number of classes and instances, both in families and in species, and create new classification problems, such as differentiating birds gender or age. Also, other deep learning models will be tested to improve the classification performance, especially at the species level.

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