DEEP LEARNING FOR BUILDINGS DETECTION IN THE SOUTH OF THE BRAZILIAN PANTANAL

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ABSTRACT

Climate changes are each more intense, and the Brazilian Pantanal has suffered from the increasing frequency of droughts. This situation alarms and concerns the occurrence of fire and its control. In 2020, a sequence of events, including droughts and high temperatures, increased the potential of fire and destruction, reducing its control and consequences. In case of a disaster, thinking in rescues, medical services, planning, and a place with challenging access, this study aims to detect buildings in a rural area of the south Pantanal using deep learning object detection-based methods. Esri Images comprised a dataset of 1247 images, divided into 60% for training, 20% for validation, and 20% for the test. A total of 939 buildings were labeled except for the urban area. The result reached an average detection precision of 0.89 for an area of 2,325 km².

Keywords — Object detection, deep learning, buildings, rural areas, mmdetection.

1. INTRODUCTION

The Pantanal is a biome in most of Brazil, considered one of the largest wetlands in the world and the habitat of rich biodiversity. The flood is the main characteristic, defining the dynamics of the Pantanal, including vegetation, animals, and rural activities. There are two distinguished seasons: the wet season and the dry season. In the wet season, the rain fills and overflows the rivers that retain the water for a longer period due to the geomorphologic characteristics. In the dry season, the water level drops, the wet areas dry up, the animals return to the plain area, the soils are fertilized, and vegetation occurs [1].

However, the biome has suffered impacts from anthropic activities and climate change. Also, annually occurs fires, around 5,3% of the Pantanal area is burned every year [2]. In 2020 extensive areas were burned, and the wildfires market the region and Brazil. According to the survey of MapBiomas [2], of the total area burned in that year, 52,6% was grasslands vegetation (campestre), 18,5% was savanna, 14,4% swampy and flooded area, 8,2% was forest, and 6,4% pasture areas.

Studies showed that the combination between heat and droughts was the reason for the wildfires in 2020 in the Pantanal. According to Libonati et al. [3], the sequence of events was decisive: a long period of a lack of rain associated with a high level of evaporation. The dry soil and dry vegetation increased the fuel load, the reduction of flood pulse, and the potential of flammability due to increasing sensible heat between the surface and the atmosphere. South America was under severe drought in most regions in 2020. In Pantanal was the highest in 60 years [4]. The drought was an environmental disaster experienced on all continents that year [5].

In the Pantanal region, the reduction of summer rains was between 50% and 60% from 2019 to 2020 [4,6]. The drought associated with high temperatures facilitates fire propagation and makes its control difficult. The projections for the situation are alarming. Marengo et al. [7] showed that between 2010 and 2040, the temperature of Pantanal would increase from 2.5° to 3.5°C, and the rain would reduce from 10% to 20%. This biome is considered one of the most preserved biomes of Brazil, and access is challenging in some areas, mainly regarding services, medical care, and fire control. These aspects concern when we think about the provision of services, assistance, and rescue.

On the other hand, computer vision techniques and artificial intelligence have been applied to environmental studies and monitoring. Object detection is a deep learning task, and this study was applied for building detection. The characteristic of object detection is locating and recognizing an instance object in an image through a bounding box. There are some studies applying this technique to the medical area, animal detection, and post-disaster mapping, e.g., after an earthquake, building detection for solar panel uses, and change detection.

Regarding this and to provide information that could be helpful, the main aim of this study is to detect the buildings in the south region of the Pantanal using deep learning object detection-based methods.

2. MATERIAL AND METHODS

2.1. Study Area

The study area (Figure 1) comprises the south region of the Brazilian Pantanal, located in Porto Murtinho city, Mato Grosso do Sul state. This region covers an area of 2,325 km², where most of the rural area has pasture characteristics. The urban area was removed from this study to focus on and not interfere with buildings of rural characteristics.

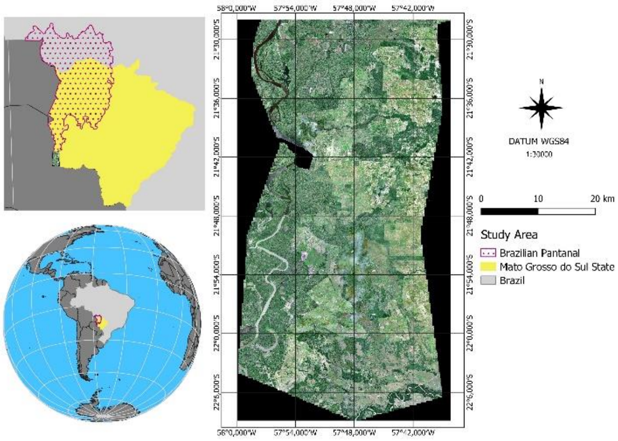

Figure 1. Location of the Study Area.

2.2. Object and Dataset Characterization

The object comprises building in the rural zone of the study area: houses, corrals, and warehouses. These buildings have different geometry (no patterns); locations are sometimes under trees, around other few buildings, trees or isolated, with different directions and sizes.

The images are Esri Images obtained through the Terra Incognita software [8], which provides various sources of maps or images for free. A total of 28 images were downloaded with approximately 1.20 meters of spatial resolution. After the download, the images were processed in ArcgisPro [9], joined as a mosaic, and labeled with 939 buildings annotated. The bounding box was used for the handmaking labeling with the unique class as 1. The clip of 512 x 512 size and overlap of 50% generated a total of 1,247 images with labels.

These images and the annotations were processed in the Roboflow [10], a conversion tool used for computer vision datasets, to convert the dataset to the coco format. In this process, the files were separated into three (3) sets: train (60%), validation (20%), and test (20%).

2.3. Application

In the next step, the sets train-validation-test were applied to the MMDetection [11], a tool dedicated to object detection and instance segmentation with the state-of-art models. The algorithm selected for the building detection is the Faster R-CNN. Proposed by Ren et al. [12], this model is the combination of the Fast-R and the RPN (Region Proposal Network), providing better precision is one of the references of the state-of-art in the object detection area. The parameters used for the Faster R-CNN were: 24 epochs, a learning rate of 0.01and SGD (Stochastic Gradient Descent).

2.4. Evaluation Method

The evaluation was performed using the average precision 50 (Ap50), one of the metrics for the object detection evaluation. This metric determines the average precision related to the recall with the interval from 0 to 1, where the closer or equal to 1, the better the result.

When the predictions agree with the ground truth, it is called true positives (TP); when the predictions do not correspond with the ground truth are false positives (FP); and when there was no detection (prediction) of an existing object in the ground truth is considered false negative (FN). The precision is the ratio of TP to the total of TP and FP. The recall is the ratio of the TP to the total of TP and FN.

3. RESULTS AND DISCUSSIONS

The performance of the detection is shown in Figure 2. According to the size of the building, the detection occurred only for medium and small building bboxes, resulting in respectively 0.97 and 0.88 of Ap50. In general, the average precision (Ap50) reached 0.89.

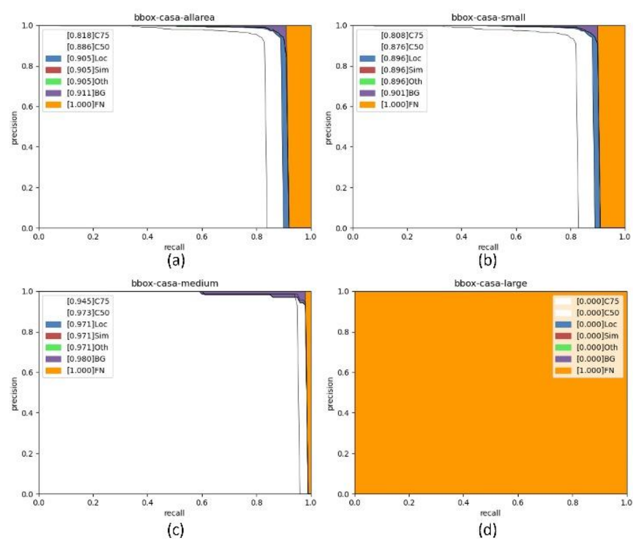

Figure 2. Values of Average Precision (Ap 50) for the general detection, and according to the size of building bbox.

The graph in Figure 3 shows the loss behavior according to the epochs processed. There are three expected scenarios: underfitting, overfitting, and good fitting. When the train and validation loss are high, overfitting occurs, indicating adaptation of the model and the need to increase the dataset. Overfitting occurs when the validation loss is higher than the training loss; the model has a good performance, however the validation loss is higher. This situation could indicate the models were trained for a long period or data complexity. The best scenario is good fitting when the training and validation decrease according to the epochs.

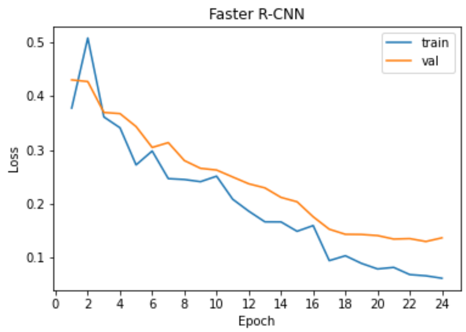

Figure 3. Graph of the Loss related to the epoch performed by the Faster R-CNN algorithm.

In this case (Figure 3), the validation and training loss is decreasing, which is the best scenario expected. Also, it is possible to verify that the iterations of more than 24 epochs could probably indicate a possible overfitting case. The behavior of the loss curve shows that 23 epochs were iteration enough for this model.

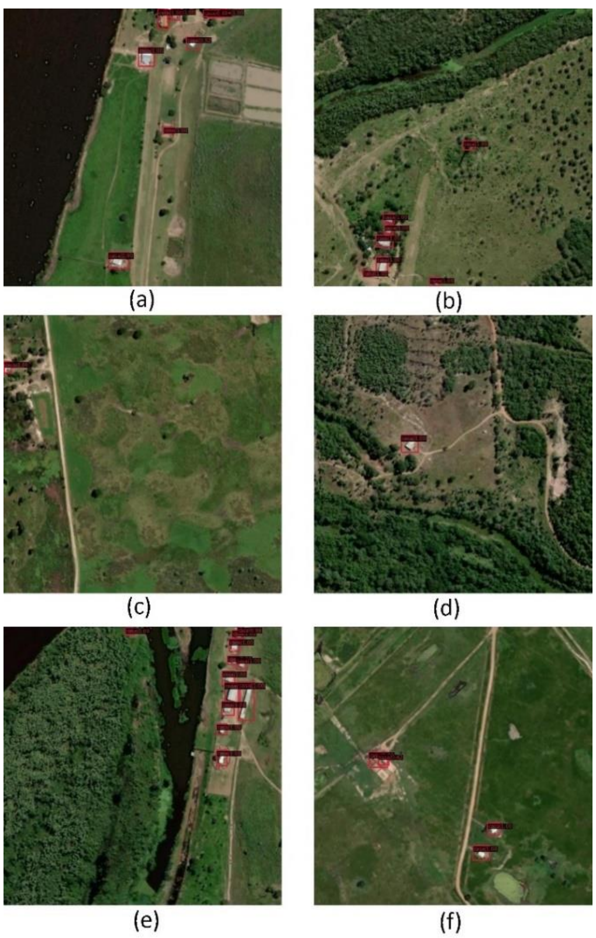

Figure 4. Selection of building detected images.

Figure 4. shows the buildings detected with different roof colors and patterns, near the river and grassland (Figure 4.a.), around trees and near other buildings (Figure 4.b.), a part of one building (Figure 4.c.), one building (Figure 4.d.), different sized of buildings (Figure 4.e.), building distance each other (Figure 4.f.). In all these situations, the values of the precision or score in each image are, in most, around 1, the maximum value.

However, the detection was challenging in some images, as shown in Figure 5. In the first image (a) of this figure, a dam was detected as a building. This detection error possibly occurred due to the shape similar to roof buildings or some existence of trees covering buildings in the training model, confusing the model. Figure 5.b. has a half part of a corral, the only building in this image not detected by the model. Different from Figure 5.c. where there are other buildings near each other, one of them was not detected. Also, in Figure 5.d. there are some buildings not detected by the model, one of them almost impossible to see due to the roof color aspects being similar to the surrounding area.

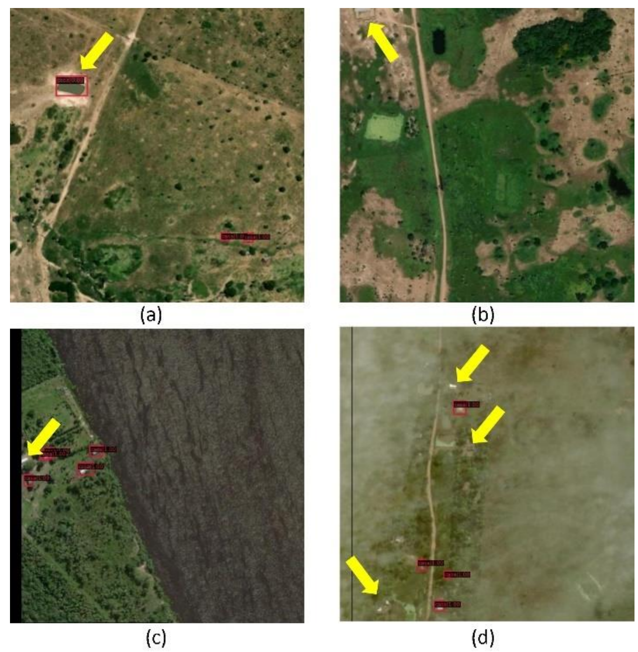

Figure 5. Challenging images with wrong or no detection.

In other images (Figure 6), despite having some elements that can represent a challenge, buildings were detected. In Figure 6.a. there are some boats similar to the buildings in the images that were not confused with our class of study. Although the clouds in Figure 6.b. make the definition of the elements as the buildings hard, it was possible to perform the detection. When we compared this image (one building) with Figure 5.d., both with clouds, despite there are some buildings not detected, it is not possible to conclude that the cloud was responsible for these no detection in Figure 5.d. It represents a challenge for the algorithm.

(a) (b)

Figure 6. Challenging images with detection.

4. CONCLUSION

Rural building detection is a challenge due to its characteristics and context. Also, some elements could be confused with the roof buildings, and other elements, e.g., tree covers, clouds, and smoke, increase the complexity and the challenge for the model. The algorithm Faster R-CNN, despite these characteristics, was able to detect rural buildings in a region of the Pantanal with an average precision of 0.89.

This methodology is a successful source of information to contribute to assistance, rescue, and medical care for that community and the region facing a disaster. A suggestion for future works is to extend this study to the entire Pantanal Biome. In addition, investigate other algorithms to improve the detection of rural buildings.

5. ACKNOWLEDGE

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