Open Cities AI Challenge: Segmenting Buildings for Disaster Resilience

March 27, 2020

1 Introduction

The development of Artificial Intelligence raises many ethical questions. Present everywhere in our professional and personal lives, artificial intelligence is playing an increasingly important role in our daily lives. This is why it is necessary to define and anticipate risks in order to prevent them. In this paper we will discuss a particular use which diverts the algorithms used for disaster risk management, for an unethical goal. The problem that we will studying can be voluntary or involuntary and can occur at different any stage of the model confection. We will be talking about: **Discriminating Models**.

Figure 1: A world with biased discriminating models

2 Problematic

We imagine here a situation where the algorithm, designed for disaster risk management, is based on biased data. This bias may be introduced intentionally or not at any stage in the confection process. One of the possible issue is creating discriminating model according to social criteria. The model will be only (or often) detecting large buildings, very showy and luxurious while ignoring poor social class housing.

This bias may be introduced in the step of data collection and pretreatment but also at the training of the model and it evaluation and even during the generalization procedure. The choice of the training set is very important to avoid this kind of discriminating models and guaranty the same quality of protection during disasters to the whole humankind bt we also must go beyond a search for performance but move towards a machine learning procedure which aims to understand and explain the demography and the distribution of inhabitants in the areas.

This approach will allow us not only to stop the creation of biased and discriminating model but will also help us to develop our understanding of phenomena and their occurrence. it is essential to move towards an artificial Inteligence created in a human understanding goal and to get away from black boxes as much as possible.

3 The impact of the use of discriminating models

Let's discuss now the impact of discrimination on people. Dealing with discrimination results in a state of heightened vigilance and changes in behavior, which in itself can trigger stress responses that is, even the anticipation of discrimination is sufficient to cause people to become stressed. In a given society discrimination may lead to an increasement of violence leading to internal problems between poor and rich people.

This kind of discrimination will be leading to splitting tendencies, the escalation of opposites and the destruction of solidarity and cohesion. In some countries of Africa, or what we call developing countries the most important factor to go further is the solidarity and the cohesion of the inhabitants, we can not allow a such division caused by discrimination if we want to really protect those countries and work for their growth and development.

Discrimination may be causing decision blocks and the loss of creativity and innovation, incentives for the "stronger" elements, and thus the prevention of communication and diversity. This may eliminate any creativity in discriminated groups so they may not be able to pursue the innovation and the development around them.

Loss of loyalty, resignation and de-motivation of employees and poor work results can also be noticed within discriminated groups which can worsen the situation notably in poor African countries, those countries need internal solidarity in order to cross the course towards a better society.

Solving disaster problem in those countries aims to improve the situation and guaranty a better condition of living but doing it in a way including discrimination may engendered the opposite effect.

4 Causes of Discriminating Models

As we said previously we can see that the causes of creating a discriminating models can occur in any step of conception process:

- **Data collection**: Collecting data must cover a large zone in order to get a vision of all the types of habitation in it. Getting only a small part of every region will not allow us to detect some habitation types which maybe more particular in a country, we take here the example of Senegal, in this country there are three types of housing :

1. regular housing-buildings-villas (62%)
2. spontaneous housing (22%)
3. village-type housing (16%)

This disproportion may be the cause of which often detect the regular housing because the training set only cover this type of housing. Here we can see the crucial role of taking consideration of the studied zone types of housing while collecting data.

- **Data Labeling**: The step of labeling the shots of drones and satellites, is a very delicate task. In fact, the whole model is based on the quality of the labeling. The label should be the more precise as possible to not introduce bias into the model during the training time. Moreover, the more the labels are detailed, the better. In fact,it's easier for the model to detect houses if there are described by different parameters like materials (wood, stone, ...).

- **Model** the bias can simply come from the model because of in homogeneity of images for one region to another. So its important to correct this bias.

5 Problems detected in competition data

While studying the given data for the challenge we noticed that many of the problems described above can be seen which my lead to creating a discriminating model or a biased one, here is some example of the noticed cases:

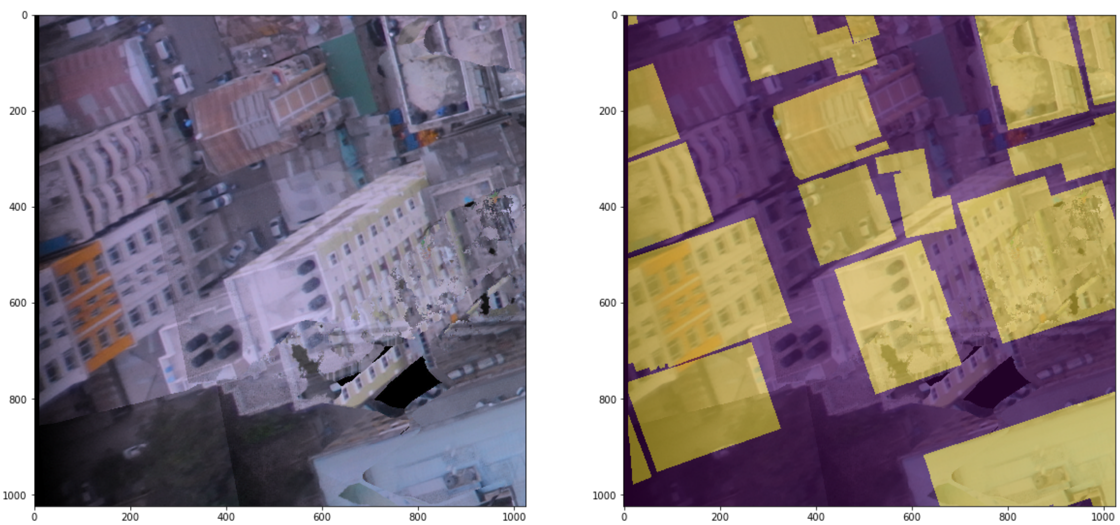

Figure 2: Bad image position leads to messy labelization

the images are not taken in a position perpendicular to the surface of the earth which creates an offset and poor labeling. Habitats in densely populated areas may not be well detected because of this phenomenon.

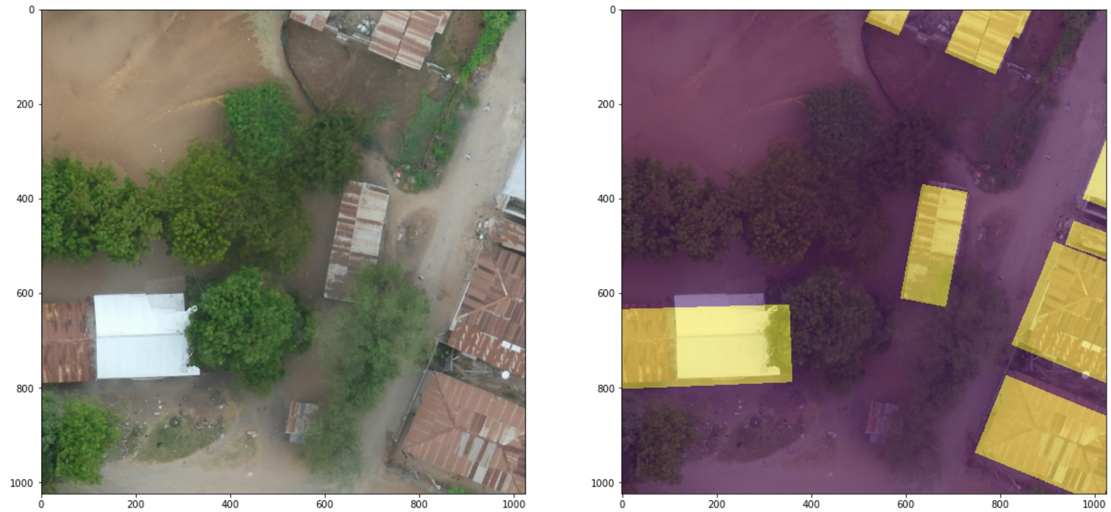

Figure 3: Ignored small houses

As we can see it clearly in the picture the labelization image do not contain a label for the small houses placed under the tree in the image. For sure, this is a consequence of the houses to being hidden by the tree, but missing a lot of small houses can create a bias we will only detect large houses around but not the small one. this may have a harmful results and unethical problems if used in As we can see here some

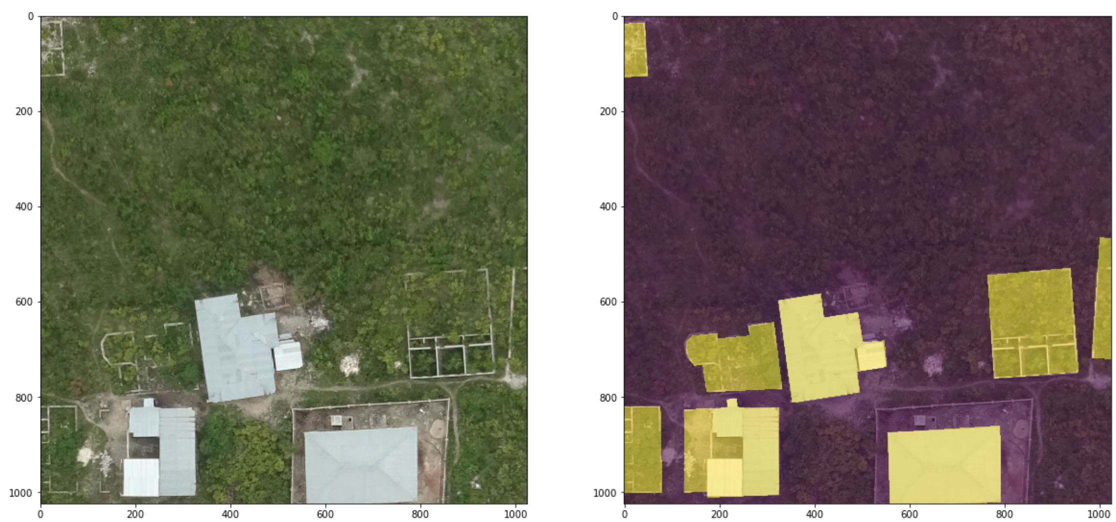

Figure 4: Labelization of free zones of construction's zones as buildings

construction's zones are labeled as buildings, this may cause a non adapted strategies while using a model based on this kid of image. Imagine in a risk situation, a big mobilisation will be used for zones with few buildings and a lot of construction zones while those resources can be used otherwise at other zones more in need.

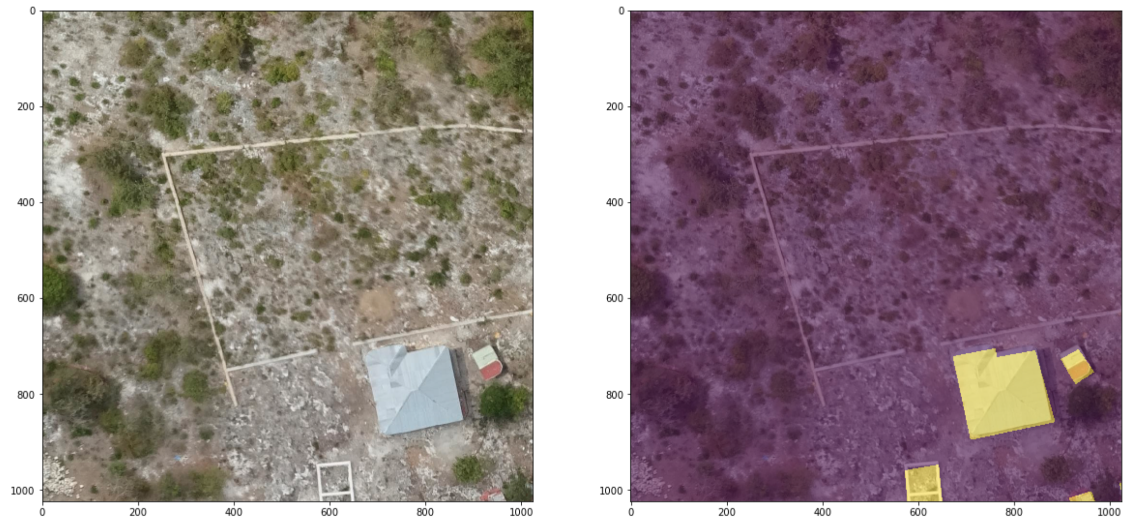

Figure 5: False labellingg

This example is a simple example of miss labeled data. what appears to be a housing area for the people who have labeled our images is none other than an area with a highly visible square delimitation. Errors of this type can be due to inattention but also to exhaustion or similar things during labeling. The repetition of images of this type, would push the model to consider all areas of square shape as areas of housing, it thus loses its usefulness and becomes handicapping for its use in disaster risk management.

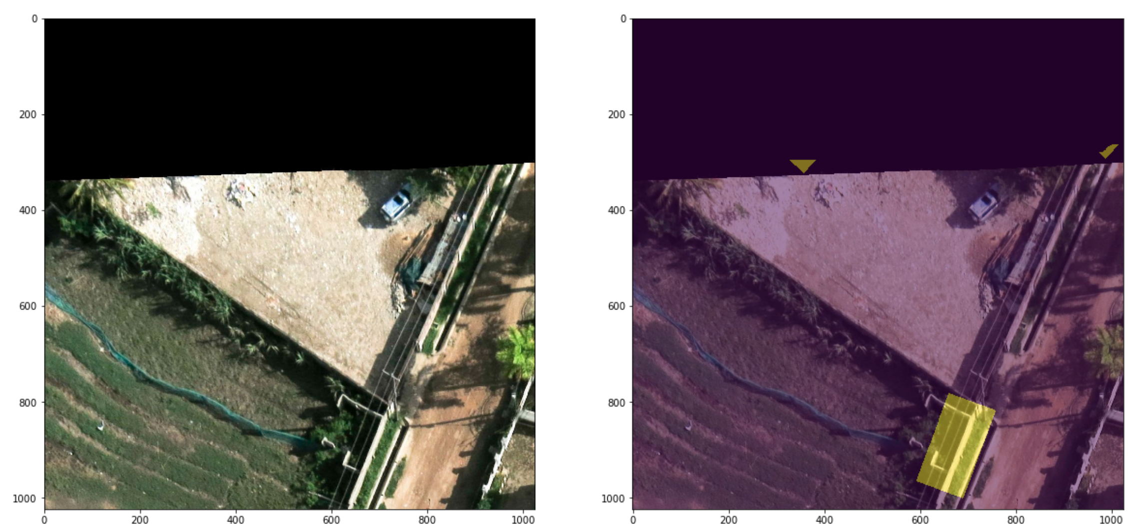

Figure 6: Repetition of labelling mistakes

Here the labeling is not clear. as seen, no house is visible on the image. Another time, it is a question of a labeling error. We see here that the errors due to this step multiply. The larger the training set, the more significant the number of inconsistencies, hence the importance given to this step. It is essential to ensure the quality of the data used before starting any experience on it. With a lot of errors, the exploited data set will lose its value and cause important unethical consequences and probably great human losses

6 Solution

We suggest some simple steps to deal with Discriminating models in the case of disaster risk management:

- Before going into complicated methods of prevision and modelization, study the region to identify all types of housing and their characteristic in order to cover all social classes.
- Checking the proportions of each type i order to avoid a biased model.
- Completing the imagery data set by information like location, material of construction to ensure the quality of the segmentation building even for the most atypical building.
- Labeling every pixel as building or not building is not enough, we may use an other labeling system based not only on existence of a building but also on the construction details and region information in order to avoid the problems described in the paper and limit their impact on results.
- Classification of housing according to some criteria to allow a better prediction, for example small houses and big houses will allow to detect in a better way small houses then the initial configuration.
- After training study the matrix of confusion in order to detect failure and their occurrence which will be relevant of bias in the model.

7 Conclusion

The risks are indeed very real, especially since modern man-machine interfaces allow immediate use of certain software solutions. But artificial intelligence will only keep its promises if the issues of fairness, interpretability, explainability and responsibility are considered at the same level as the search for efficiency. While it is still difficult to know how to design effective regulation without hampering innovation, there is no doubt that controlling risks partly involves education, training and the dissemination of a ”data and algorithm culture” with a large audience.