project-proposal_v2

July 9, 2019

1 Capstone proposal - Deep Learning for Lepus

1.1 The problem to be solved

1.1.1 (a) What are the main project idea and goals?

By thinking about the capstone project, one emerged when discussing with prof. Yves Hausser from the nature management department at hepia (HES-SO Geneva) about a deep learning project of natural images. As follows, an introduction of this project is presented:

The Lepus software [1] was designed to help scientists analyze wildlife images acquired using photographic traps. At present, species recognition and individual identification are carried out manually, which is very time-consuming. Note that, to get the data, local people have to access to these cameras and are present on some images. Thus, humans are also a category in itself and must be classified correctly.

The objective of this project is to test Deep Learning technology to automate certain tasks such as

1. detecting the presence or not of an animal/human in the image
2. locating animals/humans using bounding boxes
3. identifying certain species given a fixed taxon level
4. ideally, identify each individual animal of a specific species with respect to physical characteristics (e.g. to help the Wild Life Conservation Society) e.g. Computer Vision for Wildlife Conservation (CVWC)

Each of these problematics can be independent and with another Extension EPFL school learner (*Julien Smets/Blerim Arslani*), we decided to share this project. Here is the chosen configurations for our specific capstone projects:

Project 1 *Blerim Arslani : Detection of the presence of an animal/human in the image (binomial classification)*

Project 2 *Julien Smets : Identification of the type of an animal/human in the image (multnomial classification)*

Please let us shortly motivate our choice. By solving these two problematics, the saved time for nature management scientists could be very high (days of work), especially for the presence detection problem because only a small amount of images contains animals (this will be more deepely detailed below). Moreover, the labelled data do not include the bounding boxes which excludes the second project (here we consider only supervised learning to ensure a validation metric) and the fourth one is limited to the significant inspection variance of the manual identification and the very low amount of data available.

Note that these two chosen distinct projects are individual (will not be team-based and even the dataset will be different) and can be combined together by performing the second work right after the first one in order to classify the detected animals by assuming there is no empty images (cf. diagram as follow).

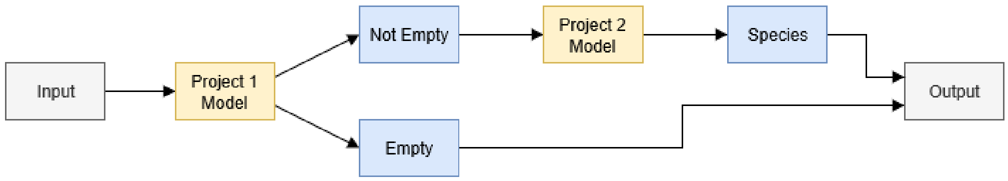


Diagram of the project

As follows, you can see the project cloud for more details:

- [1] https://lepus.cloud

1.1.2 (b) What story you would like to tell with the data and what would you like to achieve at the end?

In this second project, the aim is to classify correctly a group of animal species with the assuption that there is always an animal in the image. To this end, the idea is to: - Select potential usefull information for species identification. - Determine experiments to use this information for best accuracy possible. - Validate this experiments to obtain a powerfull model for animal identification.

1.1.3 (c) What is the main motivation behind your project?

The main idea following Lepus project is to reduce the high time consuming manual detection, localization and identification of animal species in photographic traps.

1.2 The data set

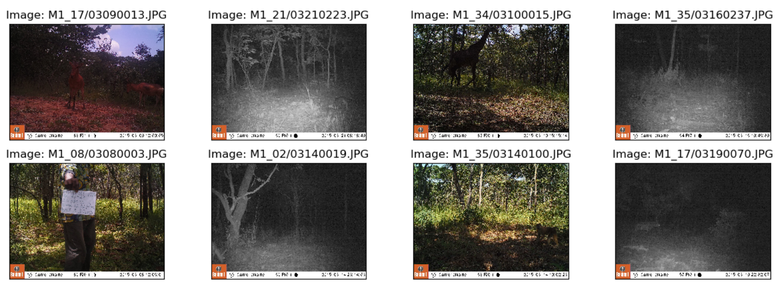
1.2.1 (a) What is the size and format of the data that you plan to use?

Data information The given species can be very small depending on the animal size and its distance to the camera or very large taking a large part of the image. Animals can be **occluded** by background objects (trees) of even be **partially viewed** (especially for large animals such as giraffes or elephants). In rare cases, it is possible to have more than one individual or more than one species in some images. The amount of species are in proportion irregular depending on the rarity of these species. Moreover, a majority of the given images doesn't contain any animals due to trees movement, dust tornado, butterflies, etc causing false positive captures. The proportion of empty pictures are **~60-85%** depending on the device environment.

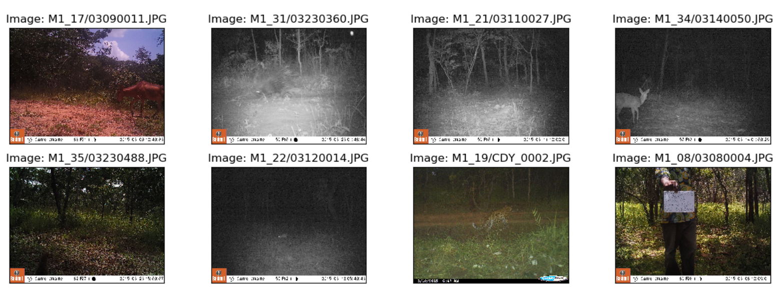
In addition, cameras have many different fields of view (FOV) and resolutions including RGB and graylevel images. The latter comes from the difference between day and night acquisition devices. Note that this results to **highly non uniform representation of species** w.r.t. different situations (day/night, background situation, etc.). As an example some species are only nocturne.

Some of the images are time correlated due to animals running and get captured several times, i.e. **small timelaps images**. These set of images are already grouped by the Lepus software. These grouped images are called **independent capture event (ICE)** and numbered from 3 up to ~300 if an animal stays in front of the camera the a long part of day/night.

Images The data set is given as image files separated in several folders and subfolders. These folder as classified by year/grid/camera/picture where a grid correspond to a set of 36 cameras (6x6). For the moment we have only one grid "M1 2015" (~2.5Gb) containing 4056 color and grayscale images with 518 (~12%) containing animals or humans. Since this amount of data is not enough for the project, a larger amount will be recieved soon. The total dataset represents a covered area of **10'000 km^2** with **hundred of cameras** placed in different nature spots in Tanzania. This data has been obtained since 2013 and until 2018 (more recent data remains unlabelled). The amount of total labelled data will come soon. The following images show a subset of the M1 2015 dataset.



Examples of images from the M1 2015 dataset.



Examples of images from the M1 2015 dataset.

Labels and other information The labels and other images information are stored in a **CSV** file.

[1]:
```
import pandas as pd
csv_file = '../submission/data/DeepLearning/DeepLearningExport.csv'
data = pd.read_csv(csv_file)
data.sample(frac=1).head()
```

[1]:
```
      file_id                     file_path session_dir   file_datetime  \
1475     1478  2015/M1/M1_25/03210797.JPG     M1 2015  21.03.15 12:22
1347     1350  2015/M1/M1_25/03200673.JPG     M1 2015  20.03.15 14:08
3945     3948  2015/M1/M1_35/03220465.JPG     M1 2015  22.03.15 11:50
1752     1755  2015/M1/M1_25/03220075.JPG     M1 2015  22.03.15 12:59
362       365  2015/M1/M1_21/03210230.JPG     M1 2015  21.03.15 11:33
```

```
     file_period  event_id  prev_file_id  session_id  place_id taxon_id  \
1475         day       221        1477.0           5        16      NaN
1347         day       215        1349.0           5        16      NaN
3945         day       511        3947.0           5        23      NaN
1752         day       224        1754.0           5        16      NaN
362          day       124         364.0           5        12      NaN

     taxon_tsn taxon_name
1475       NaN        NaN
1347       NaN        NaN
3945       NaN        NaN
1752       NaN        NaN
362        NaN        NaN
```

In the context of species identification, the **data balancing** is be an important issue. Indeed, if the data is used as is, the importance of very common speices can be significantly overestimated. As an example the perfect identification of a given species representing 80% of the data set results of an accuracy of 80% no matter how precise it is on other species. As a first step data imbalancing will be experimented.

The information of animals lifestyle is a usefull assuption used by scientists to identify species in practice. Since the camera traps are well located and include **timesteps, the day, night and twilight** can be known (see below for further details). This can also be used by adding this knowledge to infer the classification. This additional information will be tested.

The information of timelaps images can also be an informative by looking to different timelaps images, it is possible to see species moving. In a special case, the difference between these images can especially show their presence (cf. following figure).

Example of timelaps images and their difference from the M1 2015 dataset.

For this reason, this information will mostly impact the presence detection of species and will not being used in this project. Note that this can be experimented in future improvment.

Others Note that the data can need to be confidential with a DNA (standard Non-Disclosure Agreement) due to some very rare species which are often hunted for money. If this is the case, it will be demanded to the EPFL soon. But anyways the precise location of the picture will not be transmitted.

1.2.2 (b) How do you expect to get, manage and process the data?

Recieving the data The data is shared within a switch drive transfer.

Managing the data Since the whole data is shared, as a first step, the data will be cleaned and only images containing species or humans will be kept. This will be done by cleaning the CSV file. In a second step, the labels will be extracted.

Data pre-processing Images also needs processing. First of all, image will be normalized: - resize each images by downsampling the large input image into an adapted smaller shape. This will be performed empirically to balance between complexity and information loss. - normalize pixel intensities. In this case, in addition to 0-1 scaling, an adaptative contrast adjustment (CLAHE from cv2) will be computed to adjust contrast and enhance locally the visibility of hidden species. Note that it also enhance the noise in low contrast areas.

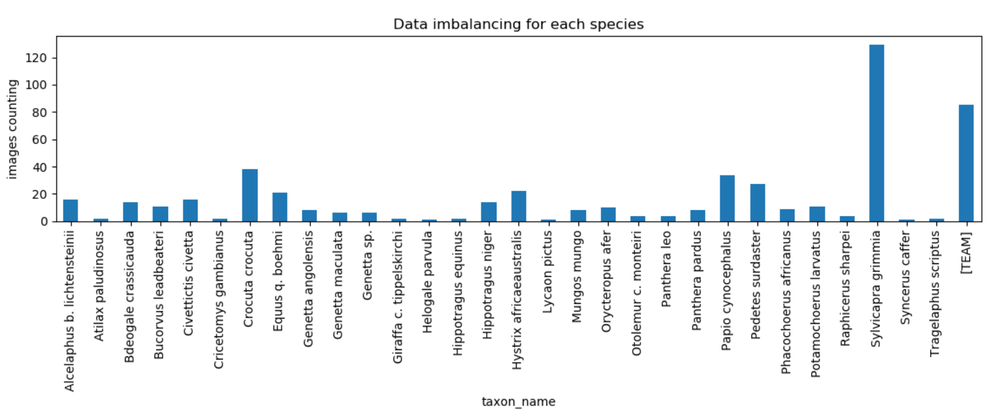
Data augmentation In the need of data augmentation, several processing are considered: - denoising. Dealing to eventual noise (e.g. due to CLAHE), it is possible reduce it by smoothing (using Gaussian kernel) and ensure the model learning denoised data. - image perturbations. Some rare species can eventually be underepresented. To tackle this issue, augmentation of the data using rotation, translation, etc. can be used (ImageDataGenerator from keras).

Additional information processing The additional data of the day/night/twilight is cyclic. Similarly to time data, it is possible to ensure locally constant difference by encoding them as day:1, twilight:0 and night:-1. This allows day and night being the highest difference possible.

1.3 The analysis and methods

1.3.1 (a) What are the main challenges that you envision for completing the project and how do you plan to get around each one?

A. Data Imbalacing Due to the location and the environment of photographic traps in addition to the different rarity of species, the distribution of the class can be significantly imbalanced (see figure as follows).



Example of data imbalancing on a grid (M1 2015) with 518 species or humans.

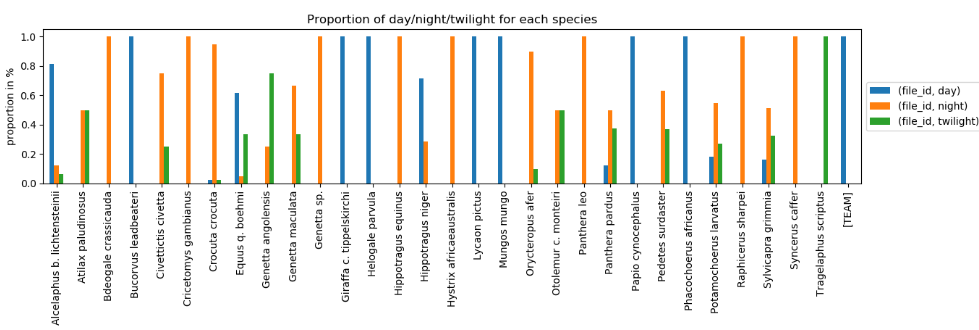
For for the seek of best identification model, it is needed to experiment the best methods to train our model. To this end, the project will include an analysis in order to determine the best way to use our data. A comparison will be preformed between: 1. unbalanced data 2. partially and fully balanced data using: * Undersampling: resample our majority classes with randomly subset selection * Oversampling: copy the minority classes images using different and small transformations (rotation, noise, blur, gray-level versions, etc.) 3. if not enough amount of images for rare species, create a group of rare species.

B. Transfer Learning, models structures and trainings approaches Instead of training on a randomly initialized model, it is common to perform transfer learning on a large challenging task pre-trained model (e.g. 1000-class ImageNet). In addition of reducing the time of training, it also helps generalization this paper. To experiment this, the following training will be performed: 1. without transfer learning (same structure with randomly initialized weights) 2. by fine-tuning (and freezing the other layers) with transfer learning on: 1. the last fully connected layers (this assumes the source and target domains are the same) and use the model as feature extractor. 2. on additionnal last layers (to be more task specific if both domains are different)

For transfer learning, one very promising model has recently been published, on June 10th 2019, and shared, on tensorflow, by Google Research called EfficientNet. This model can be scaled depending on the computer learning capability and has already been trained on 1000-class ImageNet. This can be an ideal starting point for this project.

Note that since it is also possible to experiment several other classifiers (e.g. decision tree, logistic regression, random forest, SVM, etc.), for the sake of simplicity the models will be trained only using dense layers.

C. Additional Information as Improvment Since the photographic traps are precisely located with timestamp, there is the information of solar elevation angle, thus the time of the day (day, night, twilight), which can be a powerfull information because certain species have specific lifestyle (cf. following figure).

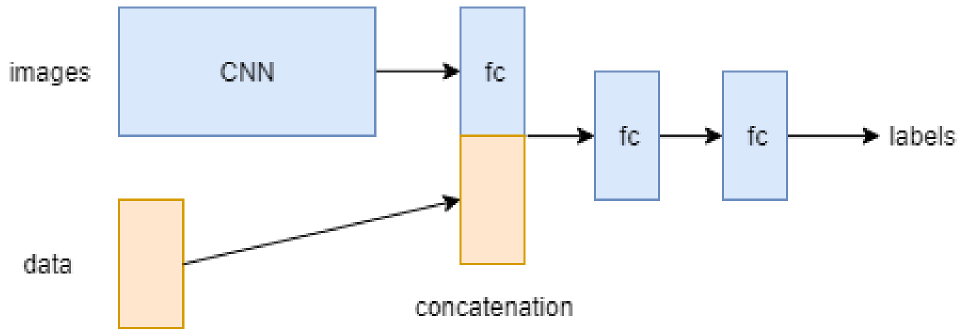


Example of day/night/twilight information on a grid (M1 2015) with 518 species or humans.

To this end, an additional experiment will be performed to determine if this information can be interesting and how it could be for the context of species classification. The following experiments will be tested to compare the accuracy between the basline CNN model: 1. without additional information 2. with concatenating directly the first fully connected (fc) layer with the information of (day, night, twilight) 3. with concatenating the solar elevation angle (computation allowing day/night/twilight changes at the approximate same time) using different machine learning methods: * decision tree * logistic regression * random forest * SVM * dense (fc) layer

The solar elevation angle should give more information since it is a (cyclic) continuous variable, in contrary to day,night,twilight which is a (cyclic) nominal feature.

The following example shows the structure of the data concatenaton (e.g. here with fc layers).



Example of the additional information utilisation as improvment on a grid (M1 2015) with 518 species or humans.

1.3.2 (b) What the are steps that you plan to take to achieve the end goals?

The steps of the work are given as follow:

1. Data **loading, cleaning and manipulation** for preparation.
2. **Preprocess** the dataset using known preprocessing steps.
3. **Split** it in train, validation and test sets.
4. Select an adapted model and use **transfer learning** for our application.
5. Train it and compute its accuracy measure. Define it as the **baseline model**.
6. **Experiment** the main challenges, validate them and test the performance of the proposed models using
   - A. different model structures and trainings.
   - B. data imbalance.
   - C. additionnal information as classification improvment.
7. **Combine** best results of A, B and C to obtain a final model. Validate and test it.

1.3.3 (c) Show us that you have a pipeline in place and that you understand the feasibility of your project goals.

1. Data Loading, Cleaning and Manipulation:

- Load CSV file and get images pathnames in several folder and subfolders using recusrive search.
- Clean data by removing unlabelled data and any without species in it.
- Manage the remaining data for easy access and processing (e.g. flow from directory).

2. Images Preprocessing:

- Select state of the art preprocessing methods adapted to our problematic (e.g.* histogram equalisation, denoising, resizing, data augmentation).

- Implement them and make them easy to use such as with flow from directory.

**based on iWildCam 2019 challenge Top7 report.*

3. Spliting the data:

- Separate the data into a stratified train/validation/test sets in order to conserve the labels (species) proportions and enviroment proportions, thus by keeping its global imbalance. This will be balanced or not depending on the experiments.

4. Transfer Learning:

- Select a state of the art pretrained model.

- Adapt the structure to our problem by adjusting last layers to fit our desired output.

5. Baseline model:

- Train the adapted model on our dataset.

- Validate the pre-trained model.

- Set this trained model as the baseline for our future experiments.

6. Experiments for our final goal:

- A. Experiment data imbalacing to set the best preprocessing method for training.

- B. Apply transfer learning, models structures and trainings approaches in order to improve the learning rate and/or the test accuracy.

- C. Use additional information to try to further improve the final accuracy.

7. Obtain our final model by comining best results:

- Use the knowledge learned by all the experiments to define a final model and compute its accuracy.

1.4 The communication

The code sample will be implemented in several python scripts (.py) for convenience and simplicity (e.g. separation of pre-processing, training and testing). An additional notebook (.ipynb) will be included with analysis details and visualization figures as a small report (similarly to this document).