Deforestation detection using residual networks

Radu-Mihai Sirbu
Babes-Bolyai University, Cluj-Napoca

Abstract

Lately deforestation has become of the most debated topics regarding biodiversity reduction, climate change and other destructive phenomena. To act against climate change, detection of deforestation is as important as reducing pollution. Therefore, this paper presents a way to detect deforestation or related events, mainly from satellite data, using a residual network based model, trained using the Amazon Rainforest dataset.

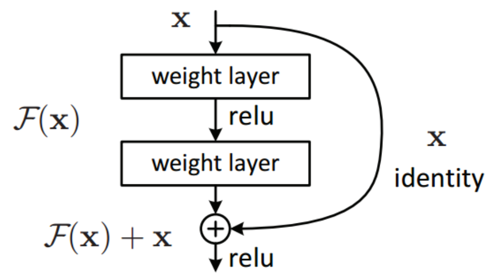


Figure 1. Example of a general residual block.

1. Introduction

In order to be able to use the residual network architecture, a large dataset is also required in this matter. What better way of training the classifier than using the Amazon Rainforest as a starting point? The Amazon Rainforest accommodates a large biodiversity and has severely been affected by the human race.

This paper will propose a multi label classification model, using 17 classes. In this way, there have been defined related labels that could indicate deforestation has occured at a certain point in time: *argiculture, mine, cultivation, road, logging, slash burn*.

The downside of using this approach is that in this case, in order to detect a deforestation case, the classified image will still have to be humanly processed so it becomes clear. However, there will be a section in this article that offers alternative ways to deforestation detection with additional resources or labeled data.

Regarding the solution, the model will be based on the ResNet50 architecture, with additional layers stacked afterwards: flatten and fully connected layers together with *ReLu* activation functions.

2. Current approaches

The deforestation detection problem has been targeted before in the literature and will continue to be targeted as long as it is needed and progress can be obtained.

Most of these approaches use temporal data, usually obtained from satellites in really high dimensions. Most of these are therefore computationally expensive and require powerful computing resources. For example some approaches use **Siamese Convolutional Networks**, **Support Vector Machines** or **Early Fusion Convolutional Networks** [3]. These approaches obtained **F1** scores of almost **50%**. However, it is worth mentioning that these approaches targeted temporal satellite images, and target deforestation specifically and not just related events.

Concerning the Amazon Rainforest dataset and the multi-label classification task, there are models in the literature based on other residual networks architecture (**ResNet18**), **MobileNet** or even an ensemble of networks together with **transfer learning**. Most of these methods are also computationally expensive, having millions of trainable parameters but eventually produce very high accuracy scores, of over **90%**.

3. Proposed solution

In order to solve the already mentioned multi-label classification problem, I will define a model based on the already existing **ResNet50**. ResNet50 is a specific type of Residual Network [2], with 50 layers. This type of convolutional neural network is made of **residual blocks** stacked on top of each other. Each block has two **3x3** convolution layers.

The main reasons for using this type of residual network are the ability to train very deep networks and the already obtained performances in other classification problems.

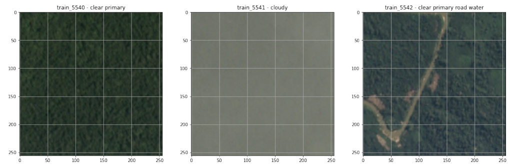


Figure 2. 3 sample images from the dataset with the associated labels.

On top of this base model, I have initially added a flatten layer, followed by 2 fully connected layers, used the *ReLu* activation function and ended with the *sigmoid* function in order to solve the classification problem.

$$Relu(x) = max(0, x) \tag{1}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

The model has also been trained using the **Adam** optimizer because of the faster computation time and **binary cross entropy** as the loss function due to the discrete outputs of the problem(labels).

4. Experiments

As mentioned before, the dataset used to solve this problem and train this model is the Amazon Rainforest dataset. It contains over **40.000** satellite pictures taken over the Amazon Rainforest, labeled using 17 different classes. Each image is a **256x256** RGB image.

The initial proposed model was trained using **1000** images, split into batch sizes of **128**, over **20 epochs** and obtained an F2 score of 0.68 which is not that satisfactory.

The second step was running a slightly different model, on more images. One of the differences is using **dropout** layers with a value of **0.2** for the threshold and add an additional fully connected layer with the *ReLu* activation function.

The model is now trained using batches of size **64** for **50** epochs that are shuffled at each step. The learning rate used in the **Adam** optimizer has also been reduced from 0.003 to 0.001 for a smoother evolution.

The amount of images would also influence the performance. Different to before, the model is trained over **5000** images which also makes this slightly altered approach more computationally expensive. The images are also scaled down to **128 x 128** pixels and have each pixel value then normalized to fit [0, 1]. The final results were therefore improved, with a score now of **0.81**, visibly greater than the one obtained before.

```
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Functional)        (None, 4, 4, 2048)        23587712

flatten_8 (Flatten)          (None, 32768)             0

dense_24 (Dense)             (None, 128)               4194432

dropout_16 (Dropout)         (None, 128)               0

dense_25 (Dense)             (None, 128)               16512

dropout_17 (Dropout)         (None, 128)               0

dense_26 (Dense)             (None, 17)                2193

=================================================================
Total params: 27,800,849
Trainable params: 27,747,729
Non-trainable params: 53,120
```

Figure 3. Updated model description.

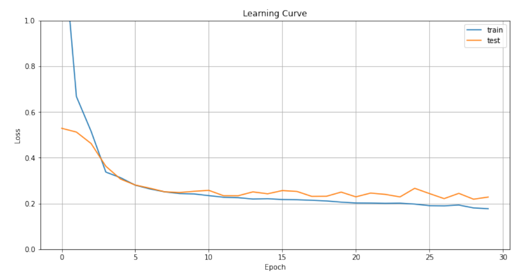


Figure 4. Graph of loss over epochs of the 2nd model version.

There were also other model variations used but proved to be less efficient:

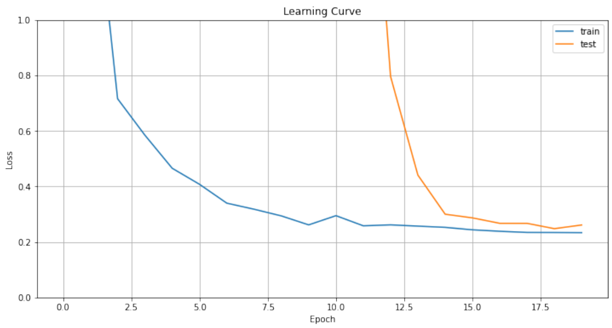
- untrainable **ResNet50** weights, initialized with the ones used for the **ImageNet** dataset [1]
- larger fully connected layers
- different batch sizes
- different loss functions(**Categorical Cross-Entropy**)

All the previous experiments were realised using google collab with GPU as the chosen hardware accelerator.

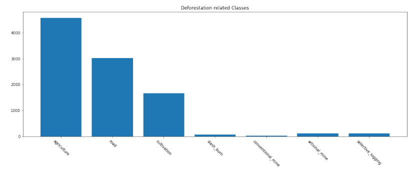
5. Conclusions

This paper presented a way of detecting deforestation using deep learning methods and architectures such as residual networks. Two different models have been presented, a simpler initial version that was trained on a smaller number of images and latter version trained over 10k images.

The dataset offered more than enough images to detect deforestation related events but the problem of deforestation itself is still not entirely solved. In order to accurately detect deforestation, one requires temporaly labeled satellite data for image comparison. Using a pair of images or maybe even a sequence of images from the same



(a) Analysis of loss over epochs when training using 1000 images.



(b) Distribution of deforestation related labels when training over 20k images from the dataset.

region from different periods can be considered a good starting point for accurate deforestation detection.

Regarding the multi-label classification problem itself, this model is outperformed by several existing architectures that even obtain scores of around **0.9** when testing. Another improvement might be the usage of different datasets, from other regions since the Amazon Rainforest region is covered by clouds most of the time during the year and therefore might need additional filters applied over the images in order to evolve the model.

References

[1] Takuya Akiba, Shuji Suzuki, and Keisuke Fukuda. Extremely large minibatch sgd: Training resnet-50 on imagenet in 15 minutes. *arXiv preprint arXiv:1711.04325*, 2017. 2

[2] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. pages 770–778, 2016. 1

[3] M. X. Ortega, J. D. Bermudez, P.N.Happ, A. Gomes, and R. Q. Feitosa. Evaluation of deep learning techniques for deforestation detection in the amazon forest. *Rio de Janeiro State University, Rio de Janeiro-RJ, Brazil*, 2019. 1