Amazon forest fire detection with an active learning approach

Matej Čerin
Jožef Stefan Institute
Jožef Stefan International Postgraduate School
Jamova 39, 1000 Ljubljana, Slovenia
matej.cerin@ijs.si

Klemen Kenda
Jožef Stefan Institute
Jožef Stefan International Postgraduate School
Jamova 39, 1000 Ljubljana, Slovenia
klemen.kenda@ijs.si

ABSTRACT

Wildfires are a growing problem in the world. With climate change, the fires have a larger range an are harder to put down. Therefore it is important to find a way to detect and monitor fires in real-time. In this paper, we explain how we can use satellite images and combine it with knowledge of active learning to get accurate classifier for forest fires. To build the classifier we used active learning like approach. We train the classifier with one labeled image. Then used a classifier to classify the set of images. We manually inspected the images and relabeled wrongly classified examples and build a new classifier. In the paper, we show that in a few iteration steps we can get a classifier that can with good accuracy identify wildfires.

Keywords

remote sensing, earth observation, active learning, rain forest, wildfires, machine learning, feature selection, classification

1. INTRODUCTION

In last years wildfires are a growing problem for the world. Each year the number of forest fires around the world grow. In recent years we had growing number of fires in Amazon, Australia, Africa and Siberia. Because of high global warming and high temperatures, the wildfires have a bigger range and are also harder to put out. Forest fires are partially responsible for the air pollution [12], loss of habitat for animals. Amazon rain forest is also called the lungs of the world, because of oxygen production by the trees. The loos of forest also connects to a higher chance of floods and landslides [6]. Therefore the classification and monitoring of wildfires is an important task. It is important to know the time series of the spread of the fire. With that knowledge we can create models for future fire events, and to plan measures in case of wildfire.

The satellite images are a good source for observation of land type [5]. Therefore they could be used for monitoring forest fires. They can be detected on satellite images, but the area of Amazon is big and it would take a lot of time to manually label burned areas by forest fires. Therefore we should develop an algorithm that can detect fires.

There are already existing algorithms for fire detection using satellite images [6, 11], they inspect changes on satellite images to detect fires. Our solution to that problem is to use machine learning. Because we do not have prepared labeled data-set active learning like approach is our next candidate.

Active learning is the approach used when the labeled data are unavailable, and labeling data is too expensive or time-consuming. The algorithm starts with a small labeled data set and then use its predictions to train itself again. That way the algorithm can learn itself. Algorithms usually need additional input for some data points. In these cases, a human should label those data, and the algorithm can then correct its predictions. The active learning approach is used in many use cases (speech recognition, information extraction, classification, ...). Over the years, it proved to work relatively well [8].

In this paper we use active learning like approach to classify wildfires. By the principle of active learning approach, we label a small subset of data and then train the classifier. Then we manually check the classification results and correct the wrongly classified examples. We then use a new bigger data-set to train the new classifier. We continue with iterations until we are satisfied with the results. That way we can iteratively get a good classifier without labeling huge amounts of data.

2. DATA

2.1 Data Acquisition

In the article, we use data from ESA Sentinel-2 mission [3]. The sentinel-2 mission produces satellite images in 13 different spectral bands with wave lengths of ligt observed from approximately 440 nm to 2200 nm. The spatial resolution is between 10 and 60 m. It consists of two satellites that circle the earth with 180° phase. One point on the earth's surface is visited at least once every five days. In future we could use also use some other satellite data sources like available at www.planet.com [1]. Those data have revisit time of 1 day and might be even better candidate for accurate monitoring of wildfires.

To download data we use eo-learn library [9] that have integrated sentinel-hub[10] library used to access satellite data. Data were downloaded for the year 2019, with a spatial resolution of 30 m. The 30 m resolution was chosen because burned areas usually extends through much bigger area than 30 m and a therefore higher resolution would not help us identify forest fires. But the processing of each image would take significantly more time than it did now.

2.2 Data Preprocessing

ESA already makes most of the preprocessing steps, like atmospheric reflectance or projection [4]. Therefore data is already clean and ready for use. For our experimentation purposes, we filtered out clouds for that purpose we used models available in eo-learn library.

In our experiments, we used all spectral bands, but the earth observation community developed many different indices that can be calculated from raw spectral bands and use them as a feature in our machine learning experiments. Indices that we used are NDVI, SAVI, EVI, NDWI, and NBR, defined in papers [7, 2]. As our feature vector we used all 13 raw bands and mentioned indices.

3. METHODOLOGY

In our experiments, we iteratively improved the classifier. In each iterative step, we looked at the images and determine if the classification was good or not. To do that most successfully we plotted the images in true color, where the burned area is usually dark, and if the fire is active the smoke is also visible. The other figure that we checked was image with RGB colors plotted Sentinel-2 bands 12, 11, and 3 (false color). Here most of the image is usually in shades of green. The burned area is dark gray color and the area currently burning is yellow or orange (Figure 2). With those two images, we have no problem checking if the area is burned or not.

We experimented with two different approaches. In the first approach, we evaluated the results of classification for each pixel and in the second experiment, we evaluated the average result for a bigger area determined with the clustering algorithm.

The classifier used in our experiment was logistic regression. We used it because it is quite an accurate classifier for earth observation and it can assess how strong the prediction is.

3.1 Experiment 1

First, we manually searched the area of the Amazon forest to find the first satellite image with a forest fire. Then we used that satellite image and labeled 270 pixels as fire area and 270 pixels as not fire area. We trained the logistic regression classifier and used it as our initial classifier in our iteration.

The iteration steps in our experiment were:
1. Use a classifier and classify pixels of a random images of the Amazon rain forest.

2. We took images that the classifier would classify with a forest fire. The images were classified as containing a burned area if at least 3 % of pixels on the image were classified as fire.

3. We checked those images and manually assigned them into two sets (true-positive and false-positive). We checked only images, where the classifier classified fire. That is because we noticed that the classifier already, in the beginning, finds fire, but it picked up some other areas and objects as fire as well. Therefore we need to find those images and label them as not fire.

4. We used a false-positive set to add to data-set the pixels that the classifier classified wrongly and true positive examples to keep the data-set balanced. We chose in each iteration the two values for the probability of prediction in logistic regression. The first value was used to determine in false-positive images to find pixels that were classified with a probability above that value to add those pixels in the data set. And the second value was used to find pixels that contained forest fire. We changed those values because the algorithm is unreliable in the first iterations and low value in the images with fire would pick up a lot of noise in the data set. But with each iteration the algorithm became more reliable, therefore we could pick lower probability without much noise. The values are shown in the Table 1.

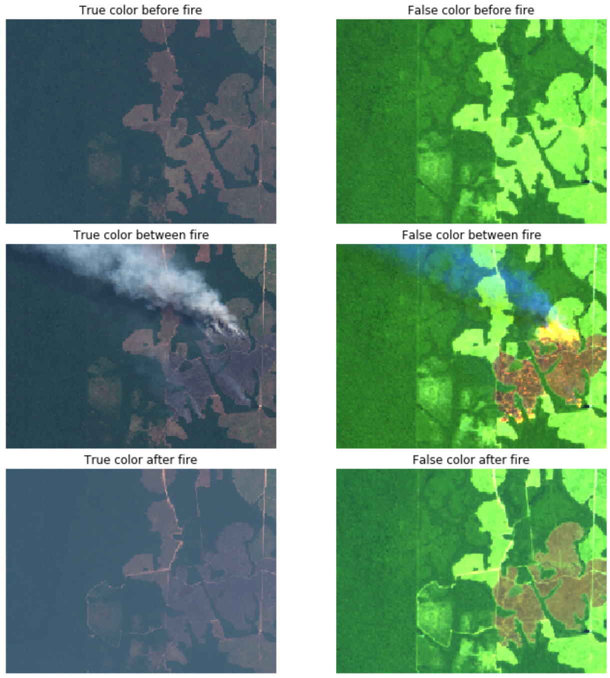

Figure 1: The Figure shows the true color and false-color images of the same area before, during and after the fire. These kinds of images can be used to manually determine burned areas.

3.2 Experiment 2

The formation of the initial classifier and the first three steps in that experiment were the same as in the first experiment.

Additional steps in the experiment are:
4. For the evaluation of the classifier, we first made clustering with the K-Means algorithm to group similar pixels on each image. The idea of that step is to use a homogeneous group of pixels that probably represent the same ground cower. Those steps are useful because we noticed that K-

Iteration	FP	TP
Iteration 1	0.0	0.80
Iteration 2	0.4	0.70
Iteration 3	0.4	0.70
Iteration 4	0.5	0.60
Iteration 5	0.5	0.60
Iteration 6	0.5	0.50

Table 1: The table shows the values of the minimum average probability of a pixel being burned area for false-positive images (FP) and true-positive images (TP).

Means usually grouped fire areas in one or two clusters. We clustered the pixels in 6 clusters. That number was chosen because on most images that number split the area that way that clusters with fire were separated from not burned area. At the same time it did not split same ground types on too many clusters.

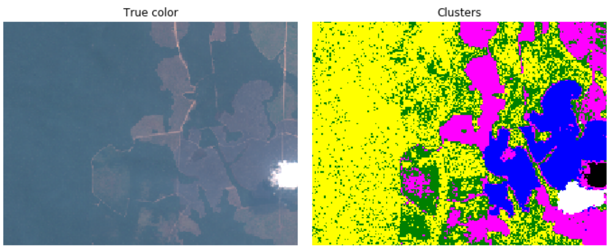

Figure 2: The figure shows how clustering groups different pixels. The burned area is all in one cluster.

5. Calculate the average probability of pixel representing forest fire for each cluster.

6. To choose what pixels to add in the data-set we once again determined two values. They defined above what average pixel probability should cluster have to add pixels from that cluster in the data set. The used values for each iteration are presented in Table 2.

Iteration	FP	TP
Iteration 1	-	0.75
Iteration 2	0.5	0.75
Iteration 3	0.5	0.60
Iteration 4	0.5	0.60
Iteration 5	0.5	0.60
Iteration 6	0.5	0.5

Table 2: The table shows the values of minimum average probability in the cluster for false-positive images (FP) and true-positive images (TP).

4. RESULTS

We tested the classifiers from each experiment on data set form the other experiment. To evaluate results we calculated F1 scores. The results are shown in Table 3.

The F1 scores are relatively high, but those data sets were constructed in a similar way, therefore the scores might be higher than they would be on real images. In both experiments we used random images from the area of amazon, therefore some images might be in both training and testing set.

	F1 score
Classifier from Experiment 1 predicting on data-set from Experiment 2	0.81
Classifier from Experiment 2 predicting on data-set from Experiment 1	0.78

Table 3: The F1 scores of classifiers.

Figure 3 depicts a time-lapse of a wildfire progress. We can see that there are some small noise pixels that are classified wrongly, but they are relatively rare.

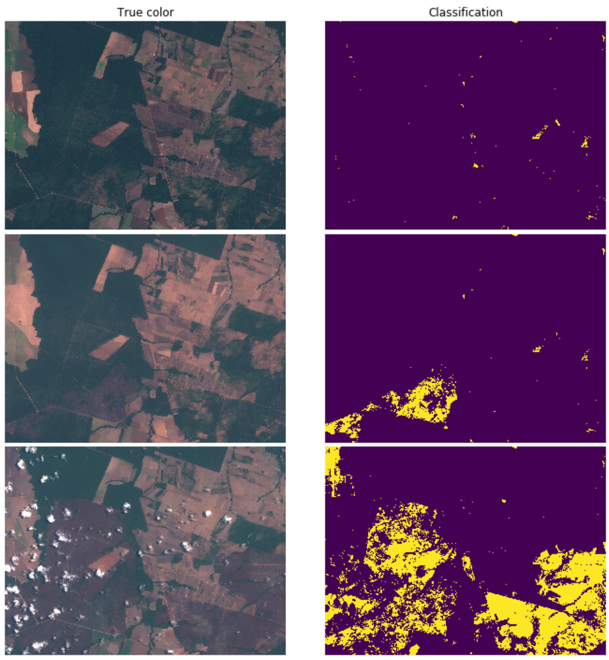

Figure 3: The sub-figures show the development of forest fire. On the left, we have true color satellite images and on the right, we have the classification result with our algorithm. yellow color depicts the burned area.

Another interesting thing to observe in our experiments is what the classifier learned and how it improved in each iteration. We noticed that in the first iterations of our experiments, the classifier did already find fire, but it also picked up many other areas as fire. One of the first improvements of the classifier was that it did not classify water areas (rivers and lakes) as fire. The other later improvements classifier were also some rocky areas. It also improved significantly in the agricultural areas, but in some cases, we could not train classifiers that there is no fire.

The classifier learned wrongly and we could not remove completely some agricultural areas and some roads in the cities. Most of the agricultural areas were classified correctly, but there were present some fields that no matter what we did were not classified correctly. This might be due to the fact that the field might be on the place that was previously burned and the algorithm still pick that up even though it was not visible from the imagery to us.

5. CONCLUSIONS

The approach with active learning seems promising and we can get relatively good classifiers in a short time. That way we could train a classifier for any classification task of satellite images. With that approach we do not need to check all images as we would if we would like to label all the data by hand. In the end, we get a relatively good classifier.

In this paper, we showed that it is possible in a relatively small number of iterations to get a good and reliable classifier of forest fires. Because satellite images are more accessible in last years than previously it could give us almost real-time insight in the Amazon rain forest.

In the feature one could use other satellite sources with better time-resolution to monitor wildfires. That way we could get more accurate view on the spread of fires.

6. ACKNOWLEDGMENTS

This work was supported by the Slovenian Research Agency and the ICT program of the EC under projects enviroLENS (H2020-DT-SPACE-821918) and PerceptiveSentinel (H2020-EO-776115). The authors would like to thank Sinergise for their contribution to EO-learn library along with all help with data analysis.

References

[1] https://www.planet.com/. Accessed 1 September 2020 .

[2] Bannari Abdou et al. "A review of vegetation indices". In: *Remote Sensing Reviews* 13 (Jan. 1996), pp. 95–120. DOI: 10.1080/02757259509532298.

[3] ESA. https://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-2/Satellite_constellation. Accessed 13 August 2018.

[4] ESA. https://sentinel.esa.int/web/sentinel/user-guides/sentinel-2-msi/processing-levels/level-2. Accessed 13 August 2018.

[5] Filip Koprivec, Matej Čerin, and Klemen Kenda. "Crop classification using PerceptiveSentinel". In: (Oct. 2018).

[6] Rosa Lasaponara, Biagio Tucci, and Luciana Ghermandi. "On the Use of Satellite Sentinel 2 Data for Automatic Mapping of Burnt Areas and Burn Severity". In: *Sustainability* 10 (Oct. 2018), p. 3889. DOI: 10.3390/su10113889.

[7] David Roy, Luigi Boschetti, and S.N. Trigg. "Remote Sensing of Fire Severity: Assessing the Performance of the Normalized Burn Ratio". In: *Geoscience and Remote Sensing Letters, IEEE* 3 (Feb. 2006), pp. 112–116. DOI: 10.1109/LGRS.2005.858485.

[8] Burr Settles. "Active Learning Literature Survey". In: (July 2010).

[9] Sinergise. https://github.com/sentinel-hub/eo-learn. Accessed 23 August 2019.

[10] Sinergise. https://github.com/sentinel-hub/sentinelhub-py. Accessed 14 August 2018.

[11] Mihai Tanase et al. "Burned Area Detection and Mapping: Intercomparison of Sentinel-1 and Sentinel-2 Based Algorithms over Tropical Africa". In: *Remote Sensing* 12 (Jan. 2020), p. 334. DOI: 10.3390/rs12020334.

[12] G. R. van der Werf et al. "Global fire emissions estimates during 1997–2016". In: *Earth System Science Data* 9.2 (2017), pp. 697–720. DOI: 10.5194/essd-9-697-2017. URL: https://essd.copernicus.org/articles/9/697/2017/.