ForestEyes Project - Citizen Science and Machine Learning to detect deforested areas in tropical forests

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***Abstract*—The conservation of tropical forests is urgent and necessary due to the important role they play in the global ecosystem. Several governmental and private initiatives were created to detect deforestation in tropical forests through analyses of remote sensing images, which demands skilled labor and different ways to deal with a great amount of data. Citizen Science could be used to mitigate these challenges, as it consists of non-specialized volunteers collecting, analyzing, and classifying data to solve technical and scientific problems. In this sense, this work proposes the ForestEyes Project [1], which aims to combine citizen science and machine learning for deforestation detection. The volunteers classify remote sensing images, and these data are used as the training set for classification algorithms. The volunteers classified more than $5,000$ tasks from remote sensing images of the Brazilian Legal Amazon, and the results were compared to a groundtruth from the Amazon Deforestation Monitoring Project PRODES. The volunteers achieved good labeling of the remote sensing data, even for recent deforestation tasks, building high-confidence labeled collections as they selected the most relevant samples and discarded noisy segments that might disrupt machine learning techniques. Finally, the proposed methodology is promising, and with improvements, it could be able to generate complementary information to official monitoring programs or even generate information for areas not yet monitored.**

I. Introduction

Tropical forests are forests located between the Tropics of Cancer and Capricorn, near the equator. They play an important role in the global ecosystem once they have great biodiversity, absorb billions of tonnes of carbon, promote cloud formation and rains, and are home to indigenous people [1]–[3].

Unfortunately, millions of hectares of tropical forests have been lost each year through deforestation and degradation due to different and complex economic reasons such as agriculture, livestock, mining, wood extraction, and others. This continuous deforestation can bring irreversible and catastrophic consequences, such as loss of biodiversity, impact on climate change due to increased greenhouse gas emissions, desertification, water scarcity, increased diseases, and even the emergence of pandemics [1], [2], [4], [5].

∗Ph.D. thesis

[1] Project's webpage with published papers: https://fafaria.wixsite.com/fabiofaria/amazon-deforestation

For the conservation of tropical forests, monitoring programs have been created, both by government agencies and by non-profit institutions. Remote sensing images, image processing, machine learning, and expert photo interpretation are used for analysis, identification, and quantification of changes in forest cover [3].

The shortage of skilled labor and the large amount of data to be analyzed is a major challenge for information and communication technologies [6]. A possible solution to this problem is to use citizen science, in which non-specialized volunteers collect, analyze and classify data to solve technical and scientific problems. It is an area that has been attracting a lot of attention due to the large volume of data generated, which is of high quality and low cost of acquisition [7], [8].

Citizen science can be a valuable source of data for the Earth Observation area, which includes monitoring deforestation. In the civic science projects ForestWatchers [3], EarthWatchers [9] and Geo-Wiki [10], volunteers analyze and classify images from remote sensing, and these classifications are used to generate deforestation maps or alerts. In the Forest Watcher project, volunteers collect data *in situ* to confirm deforestation alerts issued by the Global Forest Watch [11].

The volunteers' classifications could be used as a training set of classifier algorithms. In this context, in April/2019, the ForestEyes Project was launched, which has its Citizen Science Module hosted on the well-known platform Zooniverse [12]. Volunteers analyze and classify remote sensing images, and this data is used to train machine learning techniques that will detect deforestation in new remote sensing images.

The project was tested in areas of the Brazilian Legal Amazon, specifically in the state of Rondônia. Data from the PRODES monitoring program were used to validate the results. In this program, experts photo-interpret images from the Landsat-8 satellite, delimiting the deforestation polygons and calculating the annual rate of deforestation in the Brazilian Legal Amazon. Both annual rates and thematic images are available on the TerraBrasilis portal [13].

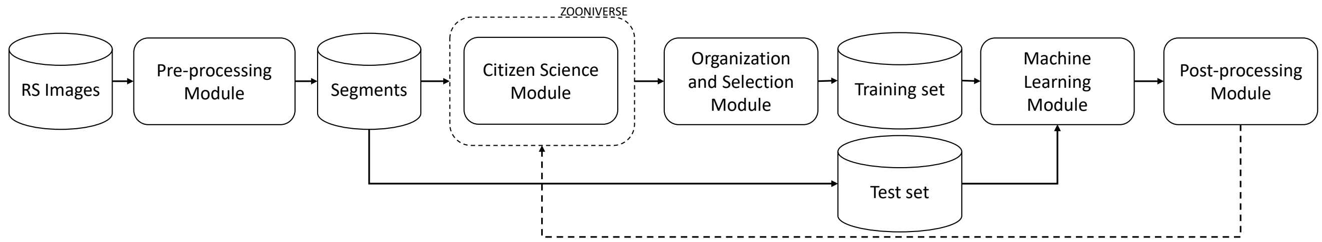


Fig. 1. ForestEyes Project's schematic representation.

II. FORESTEYES PROJECT

Figure 1 presents a general schematic representation of the ForestEyes Project, and its modules are better explained next.

A. Pre-processing Module

The steps of the Pre-processing Module can be seen in Figure 2. First, the remote sensing images are collected (step (a)). As ForestEyes is currently using PRODES data to validate the volunteers' contributions, the collected images are the ones that were analyzed by INPE's experts. These images are from the Landsat-8 OLI sensor and are freely available on the EarthExplorer platform of the United States Geological Survey (USGS).

The Landsat-8 satellite has 11 spectral bands, but only 7 bands were collected: coastal, blue, green, red, near-infrared, shortwave infrared I, and shortwave infrared II. These bands have a spatial resolution of 30 meters, that is, each pixel represents an area of 30×30 m^2. In step (b), the 7 bands undergo resampling, to be compatible with the parameters of the PRODES mosaic, and the region of interest is cropped.

As the segmentation algorithms have images of 3 bands as input parameters, it was necessary to perform a dimensionality reduction. This reduction is done at step (c) with Principal Component Analysis (PCA) [15]. The three components generated from the 7 Landsat-8 bands are then merged into one (step (d)) image, which will be the input parameter of the segmentation algorithm. Until now, 3 segmentation algorithms were tested with good results: SLIC [16], IFT-SLIC [17] e MaskSLIC [18].

From the segmented image, the segments are separated (step (e)) and stored in a database (step (f)). Some segments are sent to the Citizen Science Module, and the rest of the segments will be part of the test set of the Machine Learning Module. Currently, the selection of the segments to be sent to the Citizen Science Module is done manually. For the future, the implementation of an automatic selection method is planned.

B. Citizen Science Module

The Citizen Science Module is hosted on the Zooniverse platform. This platform was chosen due to its extensive and consolidated community, in addition to already hosting numerous Citizen Science projects.

The platform allows the creation of one or more workflows, defined as the sequence of tasks that will be performed by volunteers. In the case of ForestEyes, volunteers receive the images of the segments and must classify them among three options: Forest, Non-Forest, and Undefined. It is also allowed to add tutorials, define the number of volunteers to perform each task, zoom on the image, among other options.

A project can be public, under review (Beta Review), or an official Zooniverse project. In a public project, access is only allowed to people who have the project's link, not receiving support from the platform's community. This support is only available for official projects, which must go through Beta Review, where the platform team and a group of volunteers test and review the project. ForestEyes was sent to Beta Review in March/2018, and in April/2019, after implementing the suggested improvements, it was released as an official Zooniverse project.

In the Citizen Science Module, the selected segments are uploaded in the Zooniverse, and a new workflow is created. Each segment is a task, being represented by images with different color compositions. For all ForestEyes workflows, 15 answers are needed to complete a task, that is, 15 distinct volunteers must classify the same task.

The volunteers' answers are stored at Zooniverse and can be downloaded as a CSV file. Each line is an answer, and the columns display different information, like the id of the classification; name, id, and IP of the volunteer; volunteer's answer; analyzed task, among others.

C. Organization and Selection Module

Although ForestEyes stipulates 15 answers for each task, Zooniverse allows tasks to receive more answers. Furthermore, it is allowed for the same volunteer to answer the same task more than once. Thus, before starting the analysis of the Organization and Selection Module, filtering is performed on the responses, eliminating redundant and excessive responses, besides excluding metadata that are not important.

For now, the class of each segment is defined by the majority vote of the volunteers' answers. Other analyzes are also carried out, such as task's difficulty level, consensus convergence, volunteers' hit rates, and score, and volunteers' variability, which are detailed in [19] and [20].

With the classification of the segments, it is possible to create the training set of the Machine Learning Module. Currently, only the Forest and Non-Forest class segments are considered. For the future, it is also planned to discard segments based on other analyzes carried out, such as difficult tasks, for example.

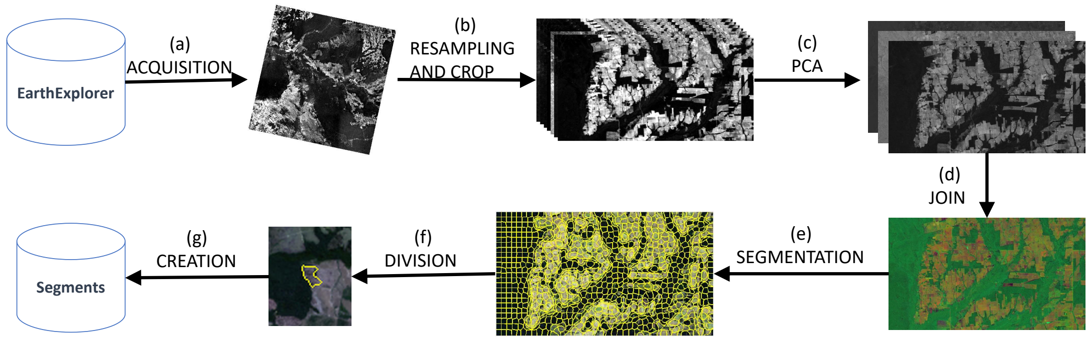


Fig. 2. Schematic representation of the Pre-processing Module steps in the ForestEyes Project. Source: [14].

The Organization and Selection Module is also responsible for comparing the volunteers' classifications to a given groundtruth. At the moment, PRODES data was used to build different groundtruth sets, which will be explained in Section II-C2. To understand these sets, it will be necessary to define a metric called Homogeneity Ratio (HoR), presented in Section II-C1.

1) Homogeneity Ratio (HoR): Only the Forest and Non-Forest classes are considered to calculate HoR. Given a segment, NP is the number of pixels that belong to this segment, NFP is the number of pixels of this segment that belong to the Forest class, and NNP is the number of pixels of Non-Forest class. As only these two classes are considered, $NP = NFP + NNP$. HoR will be the percentage of pixels of the majority class, as shown in equation (1).

$$HoR = \frac{\max(NFP, NNP)}{NP} \tag{1}$$

2) Groundtruth sets: To compare the volunteers' classifications with PRODES data, two strategies were used to define the groundtruth. The first is pixel-based. Given an image from PRODES, all classes different than Forest (deforestation, residue, hydrography, clouds, non-forest vegetation, and others) are defined as Non-Forest, resulting in a binary image that will be referred to as GT-PRODES.

The second strategy is segment-based, creating Groundtruth with Undefined (GT-U) and Groundtruth with the Majority (GT-M). These two new ground truths were created considering the HoR of each segment. With GT-U, the segments with $HoR < 0.7$ are classified as Undefined, otherwise ($HoR \geq 0.7$) are classified as the majority class (Forest or Non-Forest). As for GT-M, the segment is classified with the class that presents $HoR > 0.5$.

D. Machine Learning and Post-processing modules

The Machine Learning Module trains a classifier algorithm, which then classifies a test set. For this, firstly, the features extraction of each segment is done through the use of image descriptors, such as texture descriptors as Haralick [21] and Local Binary Patterns (LBP) [22], and the color descriptors Global Color Histogram (GCH) [23], Border/Interior Classification (BIC) [24], Mean Color and Color Bitmap (CBmap) [25]. The resulting feature vectors are normalized, and the procedure for training and applying the classifier algorithm is performed.

The classifications of the test set will be analyzed and evaluated by a future Post-Processing Module. This module can also help in future decision-making, such as a deforestation warning system. In addition, a feedback system (dashed line in Figure 1) is planned, in which interesting samples of the test set will be sent to the volunteers, to be incorporated in the training set and thus improve the classifier algorithm. The choice of these new samples to compose the training set will be carried out through active learning approaches [26].

III. Active learning approaches for deforested areas classification

To attest to the use of active learning in the scope of this thesis, different classification algorithms, and active learning approaches were tested in the classification of pixels of remote sensing images in Forest and Non-Forest. Six approaches were used, being 3 based on posterior probability (Low Confidence, High Confidence, and Hybrid Confidence), 2 based on committee (normalized Entropy Query-by-Bagging - nEQB [26] - and Committee 5CB), and one based on large margin (Margin Sampling, MS [26]). Nine different classifiers were used as k-Nearest Neighbors (kNN), Multi-layer Perceptron (MLP), Random Forest (RF), and Support Vector Machines (SVM). The results were compared with Random Sampling (RS) [20], [27].

A first experiment was carried out to build training sets from active learning approaches. An image of an area of Rondônia, in the year 2016, was used, resampled to $60m$ of spatial resolution, with groundtruth GT-PRODES. Each pixel has 7 features corresponding to the Landsat-8 OLI sensor bands.

A 5-fold cross-validation was performed where the initial training set was composed of 10 pixels (5 for each class). At each iteration, 6 samples were chosen by the active learning approaches and inserted into the training set. This procedure was repeated until 500 iterations, and the results were compared with traditional supervised learning, which used all the samples available for training.

The Low Confidence and Hybrid Confidence approaches achieved better results than RS and even presented similar results to supervised learning but using much fewer samples in the training. The High Confidence approach achieved the worst results once relevant new information is not being inserted into the classifier's training [20], [27].

The best individual classifier, RF, and Comittee 5CB were compared with the baselines nEQB and MS, which use SVM as classifier. The baselines had the best results, and Committee 5CB was the worst [20], [27].

A second experiment was carried out to test the generalization of the training sets created in the first experiment. Some training sets from the first experiment, created in the iterations 10, 20, 30, 40, 50 and 100 (cutoff points), are used to classify a new remote sensing image that encompasses more classes that aren't Forest in PRODES, such as hydrography and deforestation from years after 2012. The results were compared with supervised learning, which uses the entire set of samples from the first experiment.

Kappa and overall accuracy means were taken, with a confidence interval (CI) of 95%. The Committee 5CB and RF-low approaches obtained the best results for most cutoff points. The baselines, especially nEQB, had the worst results, with low Kappa values and accuracy, and high CI values, in addition to presenting greater instability as the number of samples increased [20], [27].

Comparing the results with supervised learning using the entire set of samples, the active learning approaches RF-low and RF-hybrid showed similar or better results than the supervised one for all cutoff points, and the SVM classifier presented the worst results. Given the obtained results, it was concluded that it was feasible to use active learning in the scope of this work [20], [27].

IV. Citizen Science campaigns of the ForestEyes Project

First, it was necessary to carry out a Beta-Review campaign. As the ForestEyes Project was inspired by the Correct Classification application of the ForestWatchers Project, the same tasks of this application were used. These tasks consisted of RGB images from the MODIS sensor, which has a spatial resolution of $250m$. Each task was delimited by a red square of size 3×3 pixels [3]. For the Beta-Review, in addition to the Forest and Non-Forest responses, the Undefined answer was created to avoid 'guesses' [20], [28].

Volunteers criticized the resolution of the image, and the way tasks were displayed. As a result, images from the Landsat-8 OLI sensor were adopted, resampled to $60m$ to be compatible with the PRODES mosaic. For better display of the tasks, the segmentation of the images with the SLIC algorithm was adopted, and the interface presented the RGB image and an image with a false-color composition, created with the shortwave infrared II (B7), near-infrared (B5), and green bands (B3) of Landsat-8. This first official ForestEyes campaign used an image of an area of Rondônia in the year 2016, being called Landsat-8 segments 2016. Then, a new campaign was created with an image of the same area but for the year 2013 (Landsat-8 segments 2013). It was thought that the difference between the images classified by the volunteers could show the areas where deforestation occurred between those years. However, this difference only identified 26% of new deforestation pixels [20], [28].

A new campaign was created in which the difficulty tasks, the Undefined tasks, and the tasks where happened ties underwent a new segmentation process through K-means clustering and the elbow method [29]. As a result, each segment from the Landsat-8 campaigns has been split into 2 or more new segments. As these new segments could be very small, only segments with a size greater than or equal to 9 pixels were sent to volunteers. The interface has also been changed, adding the 'Segment too small' response and already presenting the segments with a default zoom. Although volunteers did not achieve good accuracy in classifying these segments, by joining these new classifications with those from previous campaigns, there was an increase of more than 4% for GT-PRODES and 48% of new deforestation pixels were found [14], [20].

From 2017, the PRODES mosaic started to have $30m$ resolution, so it was no longer necessary to resample the Landsat-8 image to $60m$. In addition to the best spatial resolution, a new segmentation algorithm, IFT-SLIC, was tested. Thus, two campaigns were created: one using segmentation with SLIC (SLIC 2017) and another using IFT-SLIC (IFT-SLIC 2017). Analyzing the HoR ranges, SLIC showed a higher proportion of segments with $HoR = 1.0$ and a higher percentage of segments with $HoR > 0.7$, which may explain why volunteers better classified the tasks of SLIC 2017 campaign [14], [20].

As the goal of ForestEyes is to detect recent deforestation and the difference between two classified images proved to be insufficient to detect this type of deforestation, it was necessary to find a new segmentation algorithm. The MaskSLIC algorithm is now used since it allows the creation of an exclusion mask. Thus, for the 2017 image, a mask was created excluding all pixels of deforestation prior to August/2016. It was also adopted that the segments should have an average size of 70 pixels, which corresponds to the minimum area that PRODES detects (6.25 hectares). Many segments were generated, requiring a manual choice of segments to be sent to volunteers. In the future, an automatic procedure for this choice will be needed. A grayscale image was added to the interface, representing the Normalized Difference Vegetation Index (NDVI), where pixels closer to white are dense vegetation. With this campaign, volunteers were able to identify 65.95% of the pixels of new deforestation [14], [20], demonstrating the challenge in this type of detection, which can be explained by the remnant vegetation commonly found in the deforestation process in the Amazon rainforest [30].

A. *Results of the official campaigns*

The $5,408$ tasks received more than $86,000$ responses from 644 volunteers (174 anonymous and 470 registered), where registered volunteers contributed the most and achieved the highest hit rates. For most campaigns, volunteers' classifications achieved more than 81% accuracy for all groundtruth sets. All campaigns achieved high consensus convergence (over 90%), making it possible to decrease the number of responses needed to classify each segment [14], [20].

V. Machine Learning with Citizen Science Contributions

In this section are presented the experiments in which the segments classified by volunteers, in the campaigns Landsat-8 segments 2016 and MaskSLIC 2017, were used as training sets for machine learning techniques.

A. Experiments with Landsat-8 segments 2016

As the machine learning samples are segments, it was necessary to determine how to describe their visual properties. For this, different image descriptors were tested in a supervised learning experiment. The segments of the campaign Landsat-8 segments 2016 were used as a training set, eliminating the Undefined segments, totaling 934 perfectly balanced samples. As test sets, images of 3 new areas of Rondônia in the year 2016 were used, and the GT-M strategy was used as groundtruth.

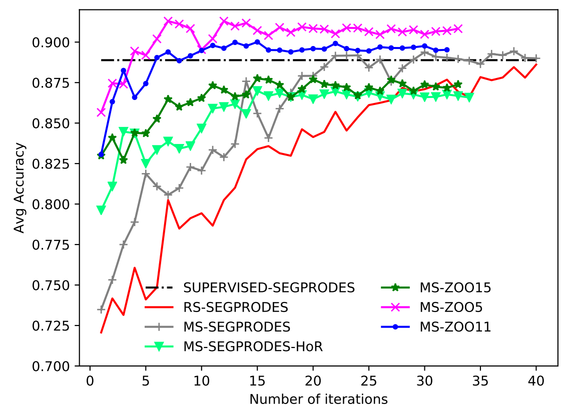
The experiments were run 30 times, and the averages of the evaluation metrics Kappa and average accuracy were calculated (mean of the accuracy for each class, Forest and Non-Forest). The descriptors LBP, GCH, and BIC had the worst results. Haralick obtained the best results, being chosen for extracting the visual properties of segments [20].

An active learning experiment was also carried out, in which the MS approach was compared with RS and supervised learning using the entire training set. The training started with 6 samples randomly selected, and at each iteration, 2 samples were inserted. The experiment was repeated 30 times, with different initial training sets, and calculating the mean value and CI of 95% of the average accuracy.

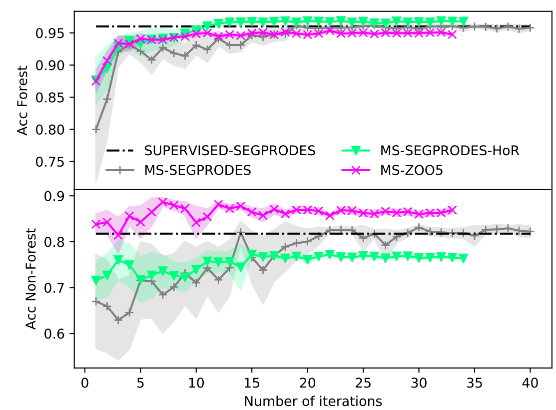
It was expected that MS would obtain a better result than RS since MS uses information to decide which samples will be included in the training. However, RS obtained results very close to MS, being raised the hypothesis that a balanced training set helped RS achieve good results. With this, two subsets of samples were created, varying the proportion between Forest and Non-Forest to $60-40$ and $70-30$. However, even with these unbalanced sets, RS remained as efficient as MS [31].

Analyzing the initial training sets, it was noticed that they were strongly or totally unbalanced, which made all samples have the same distance to the hyperplane. Thus, MS inserted in the training set the first samples in the list and not the samples that would be more representative [31].

To solve this problem, better balanced initial training sets were created through clustering with K-means and the elbow method. The elbow method, analyzing all segments, defines the number of clusters to be created through K-means. For each cluster, the segments that belong to it are divided into quartiles, considering the distance of each segment to the centroid, and then randomly choose 3 segments from the first quartile. With this better balance in the initial training, MS stood out, and the results showed a more stable behavior [20], [31].



(a) Average Accuracy.



(b) Accuracies per class (Forest and Non-Forest) with confidence interval of 95%.

Fig. 3. Results of the AL strategy (MS) using different small training datasets and two baseline techniques (Supervised learning and RS). Source: [32].

B. Experiments with MaskSLIC 2017

For these experiments, 4 areas of Rondônia in 2017 were combined into one test set, and GT-M was used as groundtruth. Also, 5 different training sets were created: ZOO15, ZOO5, ZOO11, PRODES, and PRODES-HoR. The first three refer to the classifications given by the 15, 5, and 11 campaign responses, eliminating samples different of Forest and Non-Forest. The results of ZOO5 and ZOO11 could attest to the feasibility of using fewer responses in the Citizen Science Module, which would generate data faster. The sets PRODES and PRODES-HoR use the classifications given by GT-M and GT-U, respectively, whereas, in PRODES-HoR, the undefined samples are eliminated ($HoR < 0.7$) [20], [32].

The results were unsatisfactory when performing supervised learning. A possible explanation for this was the inadequacy of the features extracted by Haralick for the classification

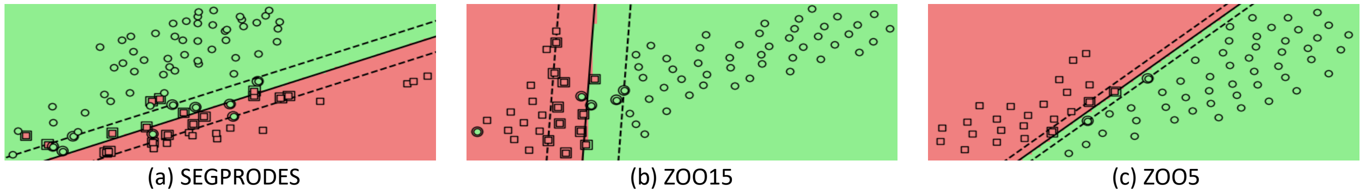


Fig. 4. Visualization of the segments present in each small training dataset represented by Haralick texture features from bands b4b6 transformed by t-SNE approach into 2D space and separated by a linear SVM technique. The square objects represent Non-forest samples, and the circle ones represent Forest. Source: [32].

of recent deforestation. The features extraction of Landsat-8 bands could bring more information to the classifier and, consequently, improve the results. Thus, different band combinations were generated, creating 135 feature vectors. To define the best combination, a supervised learning experiment was carried out, in which the combination of the Landsat-8 red (B4) and shortwave infrared I (B6) bands stood out and was chosen for the next machine learning experiments [20], [32].

For the active learning experiment, it was used an SVM classifier, K-means clustering, and elbow method to define the initial training sets. At each iteration of the active learning, 2 samples were inserted into the training set. As the set of available samples is small (up to 91 samples), it was decided to perform gridsearch of the SVM parameters in all iterations. As baselines were used the results obtained by the RS approach with the PRODES training set (RS-PRODES) and by the supervised learning with this same set (SUPERVISED-PRODES). These baselines were compared with the results obtained by the MS approach for the 5 created sets (MS-PRODES, MS-PRODES-HoR, MS-ZOO5, MS-ZOO11, MS-ZOO15).

Figure 3(a) presents the average accuracy values in which RS-PRODES has the worst results, and MS-ZOO approaches achieved the best results, with MS-ZOO5 and MS-ZOO11 being better than SUPERVISED-PRODES. In Figure 3(b), the mean of the accuracies by class and their CIs of 95% are presented. It is possible to notice the excellent result of MS-ZOO5 for the Non-Forest class, which is the target of the ForestEyes Project. Furthermore, the improvement in average accuracy for MS-PRODES in Figure 3(a) was due to a 5% gain in the accuracy of the Non-Forest class [32]. The ZOO5 set also presents excellent results in supervised learning, obtaining better accuracy in Non-Forest and better average accuracy. However, using active learning, similar or even better results are obtained using fewer samples [20].

To explain the obtained results, the t-distributed Stochastic Neighbor Embedding (t-SNE) [33] visualization tool was used. It is an unsupervised and non-linear technique that performs dimensionality reduction. The feature vectors of the training sets had dimensionality reduced from 26 to 2, and a linear SVM was applied to the generated points, obtaining Figure 4 for the PRODES, ZOO15, and ZOO5 sets. ZOO15 and ZOO5 sets have better separability between classes, especially ZOO5, which may explain the better results of this set and showing that the volunteers were able to eliminate noisy samples, which can hinder machine learning techniques [20], [32].

VI. Conclusion

This work presented the ForestEyes Project, which aims to combine citizen science and machine learning to detect deforestation in tropical forests. The results of the experiments validated the use of citizen science to build training sets at low cost and with good quality, eliminating noisy or problematic samples. Active learning is also an advantageous option since it is possible to build a training set with fewer samples and achieve similar or even better accuracies than when using all available samples. Finally, with improvements, the project can be used to complement data from official monitoring programs as well as generate data for areas not yet monitored.

VII. Publications

This Ph.D. thesis resulted in two international journal papers - IEEE Geoscience and Remote Sensing Letters [32] and Elsevier Future Generation Computer Systems [14] - and four conference papers - Conference on Graphics, Patterns and Images [27], IEEE International Conference on e-Science [28], Escola Regional de Aprendizado de Máquina e Inteligência Artificial de São Paulo [31], receiving the award of best graduate paper, and Brazilian Symposium on GeoInformatics [34].

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References

[1] C. Martin, *On the Edge: The State and Fate of the World's Tropical Rainforests*. Greystone Books Ltd, 2015.

[2] G. Urquhart, W. Chomentowski, D. Skole, and C. Barber, "Tropical deforestation," 1998.

[3] E. F. Luz *et al.*, "The ForestWatchers: A Citizen Cyberscience Project for Deforestation Monitoring in the Tropics," *Human Computation*, vol. 1, pp. 137–145, 2014.

[4] J. R. Coura and J. Borges-Pereira, "Chagas disease: 100 years after its discovery. A systemic review," *Acta tropica*, vol. 115, no. 1-2, pp. 5–13, 2010.

[5] A. Afelt, R. Frutos, and C. Devaux, "Bats, coronaviruses, and deforestation: Toward the emergence of novel infectious diseases?" *Frontiers in microbiology*, vol. 9, p. 702, 2018.
[6] M. D. Soares, R. Santos, N. Vijaykumar, and L. Dutra, "Citizen science-based labeling of imprecisely segmented images: Case study and preliminary results," in *Collaborative Systems-Simposio Brasileiro de Sistemas Colaborativos (SBSC), 2010 Brazilian Symposium of. IEEE*, 2010, pp. 87 – 94.
[7] F. Grey, "Viewpoint: The age of citizen cyberscience," *Cern Courier*, vol. 29, 2009.
[8] J. Silvertown, "A new dawn for citizen science," *Trends in Ecology & Evolution*, vol. 24, no. 9, pp. 467–471, 2009.
[9] D. Schepaschenko, L. See, M. Lesiv, J.-F. Bastin, D. Mollicone, N.-E. Tsendbazar, L. Bastin, I. McCallum, J. C. L. Bayas, A. Baklanov *et al.*, "Recent advances in forest observation with visual interpretation of very high-resolution imagery," *Surveys in Geophysics*, vol. 40, no. 4, pp. 839–862, 2019.
[10] S. Fritz, I. McCallum, C. Schill, C. Perger, L. See, D. Schepaschenko, M. Van der Velde, F. Kraxner, and M. Obersteiner, "Geo-Wiki: An online platform for improving global land cover," *Environmental Modelling & Software*, vol. 31, pp. 110–123, 2012.
[11] R. Petersen, L. Pintea, and L. Bourgault, "Forest Watcher Brings Data Straight to Environmental Defenders," http://blog.globalforestwatch.org/people/forest-watcher-brings-data-straight-to-environmental-defenders/, 2017, accessed: 08-07-2020.
[12] A. M. Smith, S. Lynn, and C. J. Lintott, "An introduction to the zooniverse," in *First AAAI conference on human computation and crowdsourcing*, 2013.
[13] A. Souza, A. M. Vieira Monteiro, C. Daleles Rennó, C. A. Almeida, D. de Morisson Valeriano, F. Morelli, L. Vinhas, L. E. P. Maurano, M. Adami, M. I. Sobral Escada, M. da Motta, and S. Amaral, "Metodologia Utilizada nos Projetos PRODES e DETER," *São José dos Campos: INPE*, 2019.
[14] F. B. Dallaqua, Álvaro L. Fazenda, and F. A. Faria, "ForestEyes Project: Conception, enhancements, and challenges," *Future Generation Computer Systems*, vol. 124, pp. 422–435, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167739X21001965
[15] I. Jolliffe, *Principal component analysis*. Springer, 2011.
[16] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Süsstrunk, "SLIC superpixels compared to state-of-the-art superpixel methods," *IEEE transactions on pattern analysis and machine intelligence*, vol. 34, no. 11, pp. 2274–2282, 2012.
[17] E. B. Alexandre, A. S. Chowdhury, A. X. Falcao, and P. A. V. Miranda, "IFT-SLIC: A general framework for superpixel generation based on simple linear iterative clustering and image foresting transform," in *2015 28th SIBGRAPI Conference on Graphics, Patterns and Images*. IEEE, 2015, pp. 337–344.
[18] B. Irving, "maskSLIC: regional superpixel generation with application to local pathology characterisation in medical images," *arXiv preprint arXiv:1606.09518*, 2016.
[19] J. S. Arcanjo, E. F. Luz, Á. L. Fazenda, and F. M. Ramos, "Methods for evaluating volunteers' contributions in a deforestation detection citizen science project," *Future Generation Computer Systems*, vol. 56, pp. 550–557, 2016.
[20] F. B. J. R. Dallaqua, "Projeto ForestEyes - Ciência Cidadã e Aprendizado de Máquina na detecção de áreas desmatadas em florestas tropicais," Ph.D. dissertation, Universidade Federal de São Paulo. Instituto de Ciência e Tecnologia, 2020.
[21] R. M. Haralick, K. Shanmugam *et al.*, "Textural features for image classification," *IEEE Transactions on systems, man, and cybernetics*, no. 6, pp. 610–621, 1973.
[22] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971–987, 2002.
[23] M. J. Swain and D. H. Ballard, "Color indexing," *International journal of computer vision*, vol. 7, no. 1, pp. 11–32, 1991.
[24] R. O. Stehling, M. A. Nascimento, and A. X. Falcão, "A compact and efficient image retrieval approach based on border/interior pixel classification," in *Proceedings of the eleventh international conference on Information and knowledge management*, 2002, pp. 102–109.
[25] T.-C. Lu and C.-C. Chang, "Color image retrieval technique based on color features and image bitmap," *Information processing & management*, vol. 43, no. 2, pp. 461–472, 2007.
[26] D. Tuia, M. Volpi, L. Copa, M. Kanevski, and J. Munoz-Mari, "A survey of active learning algorithms for supervised remote sensing image classification," *IEEE Journal of Selected Topics in Signal Processing*, vol. 5, no. 3, pp. 606–617, 2011.
[27] F. B. J. R. Dallaqua, A. L. Fazenda, and F. A. Faria, "Active Learning Approaches for Deforested Area Classification," in *2018 31st SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*. IEEE, 2018, pp. 48–55.
[28] ——, "ForestEyes Project: Can Citizen Scientists Help Rainforests?" in *IEEE 15th International Conference on eScience*. IEEE, 9 2019, pp. 18–27.
[29] T. M. Kodinariya and P. R. Makwana, "Review on determining number of Cluster in K-Means Clustering," *International Journal*, vol. 1, no. 6, pp. 90–95, 2013.
[30] M. Ortega Adarme, R. Queiroz Feitosa, P. Nigri Happ, C. Aparecido De Almeida, and A. Rodrigues Gomes, "Evaluation of Deep Learning Techniques for Deforestation Detection in the Brazilian Amazon and Cerrado Biomes from Remote Sensing Imagery," *Remote Sensing*, vol. 12, no. 6, 2020. [Online]. Available: https://www.mdpi.com/2072-4292/12/6/910
[31] F. B. J. R. Dallaqua, A. L. Fazenda, and F. A. Faria, "Aprendizado Ativo com dados de Ciência Cidadã para o monitoramento de florestas tropicais," in *1ª Escola Regional de Aprendizado de Máquina e Inteligência Artificial de São Paulo (ERAMIA-SP 2020)*, 2020.
[32] ——, "Building data sets for rainforest deforestation detection through a citizen science project," *IEEE Geoscience and Remote Sensing Letters*, pp. 1–5, 2020.
[33] L. Van der Maaten and G. Hinton, "Visualizing data using t-SNE." *Journal of machine learning research*, vol. 9, no. 11, 2008.
[34] F. B. J. R. Dallaqua, A. L. Fazenda, and F. A. Faria, "Projeto ForestEyes: Uma proposta para aliar ciência cidada e aprendizado de máquina para monitoramento de desmatamento," in *Proceedings XXI Brazilian Symposium on GeoInformatics (GEOINFO)*, 2020.