Understanding the Amazon from space

**Abstract:** Deforestation in the Amazon Basin has severe consequences on biodiversity, habitat loss, climate change, and other devastating effects. Timely and accurate monitoring of deforestation is critical for effective response. In this research, we propose a solution to the Planet dataset challenge, which involves classifying satellite images to identify deforestation and land cover / land use classes. We employ a convolutional neural network (CNN) //Clarify model trained on a subset of the dataset, leveraging it’s ability to learn spatial patterns on images. The model is augmented with data augmentation techniques //Clarify to enhance its generalization capabilities. Our results demonstrate promising performance in identifying deforestation.

1. **Introduction**

Deforestation in the Amazon Basin accounts for a significant loss of forest cover, contributing to reduced biodiversity, habitat loss, climate change, and other devastating effects. Accurate monitoring of deforestation and understanding its causes and patterns is crucial for effective response and conservation efforts. The availability of high resolution satellite imagery, such as the Planet dataset, presents an opportunity to leverage machine learning techniques for automated deforestation detection and land cover / land use classification.

The dataset is based on pictures of the Amazon basin taken by the Flock 2 geostationary satellite. Each image was then split into 256x256px ‘chips’ for ease of use by machine learning algorithms, then each of these chips is labeled with each of the //17 classes of land use specified by the Planet team.

When solving satellite image classification problems, it’s common to rely on convolutional neural networks. One of the benefits is that we can use a pretrained CNN with either no modification at all or with retraining some of the final layers and have a powerful feature extraction layer. On top of the CNN a shallow neural network or even an XG Boosted decision can classify chips with accuracy percentage in the high eighties to low nineties.

Since it has been observed that Efficient Net can retrain its top layers faster, and using another CNN offers little to no benefit in accuracy, we chose Efficient Net as the feature extraction layer.

// Kakvo sme polzvali nad neq, intro

1. Dataset:

Each chip in the dataset corresponds to an area of 89.72 hectares (947 by 947 meters). The training and test datasets contain 40,799 and 40,669 images each. /\*има test-additional dataset, не знам на какво точно отговаря\*/ While at its raw state the dataset contained over 150,000 images, the Planet team chose to discard some of them and crowdsourced the labelling of the rest. There are 17 possible labels – four of them (‘clear’, ‘haze’, ‘partly cloudy’ and ‘cloudy’) refer to the level of cloud cover in the image. Another six ('agriculture’, 'bare\_ground', 'cultivation', 'habitation', 'primary', 'water', ‘road’), with ‘primary’ referring to jungle, represent the bulk of land use, and are as such rather common. The following four ('artisinal\_mine', 'conventional\_mine', 'selective\_logging', 'slash\_burn') refer to more specific and more rarely observed types of land use. The last two labels (‘blooming’ and ‘blow\_down’) are for peculiar and transient natural phenomena. As such the dataset is rather unbalanced in favor of some classes over others. A picture containing text, screenshot, map

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These chips are available in both .jpg and GeoTiff formats. The latter contains an additional near-infrared color band which could potentially increase the model’s accuracy but ultimately we decided on training our model on the .jpg since it simplifies the training process as they can be directly fed into a pre-trained CNN without need for pre-processing, and their higher availability would make it more practical for future use (for example even the torrents for the Planet dataset in GeoTiff are barely seeded and may require more than a day to download)

1. Data augmentation

Some ideas we explored included artificially increasing the size of the training dataset by rotating and mirroring its chips. Doing so would preserve the labels on it and provide up to a sevenfold increase in the number of training chips. /\*ще го пробвам утре, ако не помага особено – ще отбележим\*/ We also explored [grayscaling, shrinking to 128x128, whatever] and …

1. Training

//TODO: Sunday

1. Results
2. Application and further development