Deep Learning for Deforestation Detection using Planet Amazon Satellite Imagery

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Abstract

Deforestation is a big environmental issue impacting climate, wildlife, and ecosystems worldwide. Traditional methods of tracking deforestation often miss early signs because they use low-resolution images. This project uses detailed satellite pictures from Planet Labs and advanced deep learning (CNNs) to spot deforestation earlier and more accurately. Our method looks at small image patches and quickly identifies signs of deforestation, helping to catch issues sooner. While we're testing this method in the Amazon Rainforest, it can easily be adapted to other areas around the world.

1. Introduction

Deforestation is a major global problem affecting climate, biodiversity, and human life. It causes greenhouse gases to rise, destroys habitats, and disturbs water cycles. Current systems for tracking deforestation, like Brazil's DETER, have made good progress but struggle to detect small or early signs of forest loss. This is mostly because the satellite images used aren't detailed enough or updated frequently.

These smaller events, such as selective logging, add up quickly and cause significant damage over time. Catching these early is important for stopping deforestation before it spreads. To address this, we propose using high-resolution satellite images from Planet Labs and deep-learning algorithms called convolutional neural networks (CNNs).

Planet Labs provides images with 3–5 meter resolution, much clearer than traditional satellites like Landsat or MODIS. CNNs are great at recognizing patterns in images, making them perfect for spotting subtle signs of deforestation. Although our initial tests focus on the Amazon Rainforest, our method can be used anywhere, making it a powerful tool for global environmental monitoring.

2. Related Work

Supervised Patch-Level Classification:

Previous studies often focus on supervised patch-level classification using labeled satellite images to identify deforestation.

- I. McCallum et al. (2023), "Crowd-Driven Deep Learning Tracks Amazon Deforestation," Remote Sensing.
- Loh and Soo (2017), "Amazing Amazon: Detecting Deforestation in our Largest Rainforest," CS231n Stanford.

The proposed approach differs from these because we use high-resolution images from Planet Labs, aiming for greater detail and early detection capability.

Semantic Segmentation Approaches:

Other works focus on pixel-level classification (semantic segmentation) to precisely identify deforestation boundaries.

- F.H. Wagner et al. (2023), "Mapping Tropical Forest Cover with Planet NICFI Images," Remote Sensing.
- I.M. Jelas et al. (2024), "Deforestation detection using semantic segmentation techniques," Frontiers in Forests.

Our approach differs as we simplify the classification to patch-level, significantly reducing complexity and computational resources required.

Change Detection Models: These studies compare before-and-after images to detect changes indicating deforestation.

- Z. Wang et al. (2023), "SiamHRnet-OCR: Deforestation Detection Model," Remote Sensing.
- G. Carter et al. (2024), "Detection of forest disturbance across California using PlanetScope imagery," Frontiers in Remote Sensing.

Our method differs because we primarily focus on single timepoint imagery to simplify the detection process, allowing easier adoption in resource constrained environments.

3. Methods

3.1. Dataset

We explored several available satellite datasets and selected the **Planet Amazon Rainforest dataset** for our study. This dataset includes over 40,000 satellite images (chips), each 256×256 pixels, with RGB and near-infrared (NIR) channels. Each chip has labels like primary forest, agriculture, mining, clear-cutting, cloudy, and more. We specifically identify images labeled with deforestation-related terms such as "slash-and-burn" and "selective_logging" as indicators of deforestation. Other datasets we can consider are NASA and EU Copernicus combined with forest-loss labels from Global Forest Watch, but Planet Labs gives us superior image resolution and label detail.

3.2. Model Architecture

We plan to utilize a ResNet-50 convolutional neural network (CNN), known for its effective image recognition performance. This model has already been trained on the extensive ImageNet database, which helps it quickly learn relevant image patterns. To adapt ResNet-50 to our specific dataset, we will add an additional input channel to accommodate the data, enhancing the model's ability to differentiate vegetation types.

ResNet-50 employs residual connections, which help to prevent common issues in deep learning models like vanishing gradients, allowing the model to effectively learn complex patterns crucial for detecting subtle signs of deforestation. We anticipate that this deeper architecture will significantly outperform simpler CNN structures by capturing intricate spatial details in satellite imagery.

To further improve the performance and ensure the robustness of our model, we also plan to explore minor adjustments like fine-tuning hyperparameters, adjusting layer structures, and experimenting with different types of activation functions, although the base architecture will remain ResNet-50.

3.3. Training Procedure

We will train our CNN using binary cross-entropy loss, suitable for classifying images into deforestation or no-deforestation categories. We use Adam optimization due to its efficiency and ease of use. To manage class imbalance (fewer deforestation examples), we plan to use balanced mini-batches, ensuring our model gets sufficient examples of deforestation during each training iteration.

Additionally, we will apply data augmentation techniques like random flips, rotations, and zooms. This step helps the model generalize better by recognizing deforestation from various angles and conditions. Early stopping will be used to avoid overfitting and maintain model accuracy.

4. Experiments

4.1. CNN vs. Baseline Methods

Main purpose: The main purpose is to demonstrate our CNN model's effectiveness by comparing it against two simpler baseline methods:

1. A trivial classifier always predicting no deforestation (to check class imbalance impact).
2. A threshold-based method using NDVI, a common vegetation index.

Evaluation Metrics: We will use accuracy, precision, recall, and F1 score. These metrics together will show the model's capability to detect actual deforestation (recall), avoid false alarms (precision), and balance both (F1 score). Accuracy provides an overall effectiveness measure.

4.2. Qualitative Analysis of Predictions

Main purpose: We plan a qualitative analysis to visually verify the model's predictions. By comparing CNN-generated labels with human-verified ground truths, we ensure the model accurately captures deforestation patterns rather than irrelevant features.

Evaluation Metrics: Visual inspections alongside accuracy, precision, and recall metrics will help identify specific image types where the model excels or struggles.

References

[1] I. M. Jelas *et al.*, *Frontiers in Forests and Global Change*, vol. 7, 2024.

[2] I. McCallum *et al.*, *Remote Sensing*, vol. 15, no. 21, 2023.

[3] Z. Wang *et al.*, *Remote Sensing*, vol. 15, no. 2, 2023.

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[5] G. Carter *et al.*, *Frontiers in Remote Sensing*, vol. 5, 2024.

[6] A. Loh and K. Soo, *CS231n Deep Learning for Vision class report*, Stanford University, 2017.