Understanding the Amazon from space

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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 the types of land cover and use. We experimented with both custom and pre-trained convolutional neural networks (CNN) trained on the Planet dataset, leveraging their ability to learn spatial patterns on images and reached sufficiently high accuracy for the model to be useful for detecting deforestation.

1 Github repo

https://github.com/zyppyvids/AmazonForestClassifier

2 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 and land use classification.

When solving satellite image classification problems, it's common to rely on convolutional neural networks. One of the benefits is that we can use an existing 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.

3 Dataset

The Planet dataset is based on pictures of the Amazon basin taken by the Flock 2 geostationary orbit satellite. Each image was then split into 256x256 pixel 'chips' for ease of use by machine learning algorithms, then each of these chips is labeled with each of the seventeen classes of land use specified by the Planet team.

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. 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.

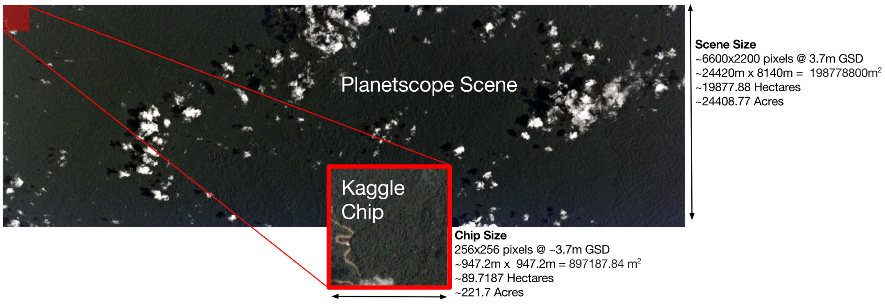

Figure 1: Examples of a chip extracted from a larger satellite image

Of the 17 types of land use that the model should recognise four refer to the level of cloud cover in the image:

$$'clear'\ 'haze'\ `partlycloudy'\ `cloudy'$$

Every image has been labeled with one of these, as it is quite important to be able to gauge the visibility over any specific place - any good well trained model should be able to recognize that the scene is too cloudy to classify anything underneath.

Another six (with ‘primary’ referring to jungle), represent the bulk of land use, and are as such rather common:

$$'agriculture'\ 'bare\_ground'\ `cultivation\ `habitation'\ `primary'\ `water'$$

The following four refer to more specific and more rarely observed types of land use.

$$'artisinal\_mine'\ 'conventional\_mine'\ `selective\_logging'\ `slash\_burn'$$

Selective logging is obviously preferable over full on land clearane, while slash and burn agriculture is potentially much more destructive than standard agriculture.

The last two labels are for peculiar and transient natural phenomena - large concentrations of blooming plants and sections of forest flattened by high speed winds.

$$'blooming'\ 'blow\_down'$$

As such the dataset is rather unbalanced in favor of some classes over others. However even the capability to differentiate between natural cover and land use by humans can be useful for a deforestation focused application.

Figure 2: Examples of chips.

4 Methodology

4.1 Data Preprocessing

The Planet dataset comprises high-resolution satellite imagery, consisting of four spectral bands: red, green, blue, and near infrared. To prepare the data for model training, we perform the following preprocessing steps:

- Resize the images to a fixed resolution of 128x128 pixels. This standardization ensures consistent input dimensions for the CNN model while preserving important spatial information.
- Split the data into training and validation sets using an 80:20 ratio. This division allows us to evaluate the model's performance on unseen data and prevent overfitting.

4.2 Convolutional Neural Network

We construct a CNN model tailored for the deforestation monitoring task. The architecture comprises multiple convolutional and pooling layers, followed by fully connected layers. The final layer employs a sigmoid activation function to predict the presence of each land cover/land use class.

The CNN model is trained using the Adam optimizer, which adapts the learning rate dynamically during training. To optimize the model's ability to distinguish between deforestation and other classes, we employ the binary cross-entropy loss function. The loss function quantifies the discrepancy between the predicted and true labels, guiding the model's weight updates.

4.3 Data Augmentation

Data augmentation plays a crucial role in enhancing the model's generalization capabilities, particularly when the available training data is limited. By applying random transformations to the training images, we effectively increase the diversity of the dataset and expose the model to a wider range of variations. The following data augmentation techniques are employed:

- Horizontal and vertical flips to account for potential variations in orientation.

- Rotations within a certain range to simulate different viewing angles.
- Zooming to mimic variations in scale and perspective.
- Shearing to simulate distortions caused by terrain or sensor angles.

During model training, the data augmentation techniques are applied on-the-fly, generating augmented images in real-time. This diversifies the training dataset, reduces overfitting, and improves the model's ability to generalize to unseen images.

4.4 Custom model - structure and results

```
train_datagen = ImageDataGenerator(
    rescale=1./255,
    horizontal_flip=True,
    vertical_flip=True,
    rotation_range=40,
    zoom_range=0.2,
    shear_range=0.2)

model = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(
        32, (3, 3),
        activation = 'relu',
        input_shape = (image_size[0], image_size[1], 3)),
    tf.keras.layers.MaxPooling2D(2, 2),
    tf.keras.layers.Conv2D(
        64, (3, 3),
        activation='relu'),
    tf.keras.layers.MaxPooling2D(2, 2),
    tf.keras.layers.Conv2D(
        128, (3, 3),
        activation = 'relu'),
    tf.keras.layers.MaxPooling2D(2, 2),
    tf.keras.layers.Conv2D(
        128, (3, 3),
        activation = 'relu'),
    tf.keras.layers.MaxPooling2D(2, 2),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(
        512,
        activation = 'relu'),
    tf.keras.layers.Dense(
        num_classes,
        activation = 'sigmoid')
])
```

Using the the custom model we achieved 60% accuracy after training for 30 epochs.

Loss	Accuracy	F-Beta score
0.1076	0.5967	0.5913

4.5 Using EfficientNet

Additionally, we wanted to evaluate the capabilities of at least one existing neural network, and since it has been observed that Efficient Net can classify images or retrain its top layer using less computing power than other CNNs, while also losing little to no accuracy, we also experimented with efficient net and observed significantly higher accuracy, as well as an f-Beta score above 85%, proving, as we had expected, that large pre-trained CNNs are quite adept at solving this type of problem.

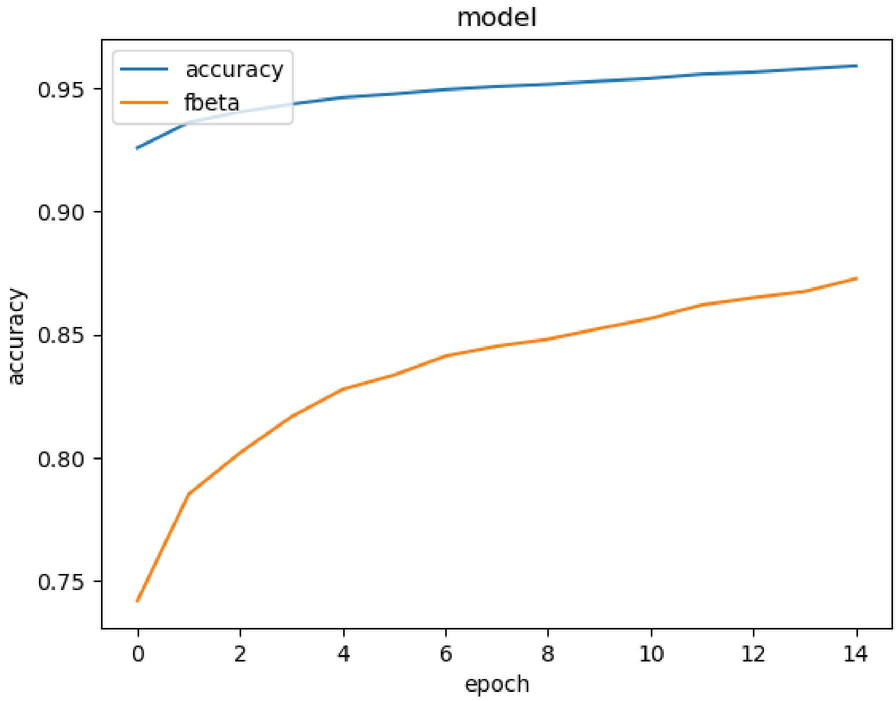

Figure 3: Accuracy and F-beta score of efficientNet based approach

5 Conclusion

In this research, we proposed several solutions for deforestation monitoring in the Amazon Basin using a CNN model trained on the Planet dataset. By leveraging the power of CNNs and augmenting the dataset with data augmentation techniques, we achieved promising results in identifying deforestation patterns and classifying land cover/land use classes.

The utilization of high-resolution satellite imagery and deep learning techniques presents a valuable tool for monitoring deforestation and aiding conservation efforts. Our approach contributes to the understanding of deforestation patterns and can support decision-making processes for environmental conservation and sustainable land use.

Future work could involve further optimizing the model architecture, incorporating additional data sources, and extending the solution to monitor deforestation in other regions. On top of that, a dedicated application could be created which will use the models we already created.

6 Discussion

Our approach to deforestation monitoring using a CNN model trained on the Planet dataset showcases the potential of machine learning techniques in addressing complex environmental challenges. By leveraging the spatial patterns learned by the CNN, our model demonstrates the ability to identify deforestation areas and classify land cover/land use classes accurately.

The effectiveness of our model can be attributed to several factors. Firstly, the high-resolution satellite imagery provided by the Planet dataset enables detailed analysis of the Amazon Basin, aiding in precise deforestation detection. Additionally, the CNN architecture captures spatial dependencies and hierarchies, allowing the model to learn meaningful representations from the imagery.

Data augmentation techniques play a critical role in enhancing the model's generalization capabilities. By introducing variations in the training data through flips, rotations, zooming, and shearing, we expose the model to diverse scenarios and improve its ability to handle real-world variations.

Despite the promising results, there are several avenues for further improvement. The model's performance can be enhanced by refining the architecture, such as incorporating deeper or more specialized layers. Additionally, exploring ensemble techniques, where multiple models are combined, could potentially boost accuracy and robustness. Integration of other data sources, such as weather and terrain data, could provide valuable contextual information for more accurate deforestation monitoring.

7 Resources

1. While working on this project the following repository and the linked articles were especially useful, but none were quoted directly: Techniques for deep learning on satellite and aerial imagery

2. The overview of the problem and datasets by Planet was also crucial: Planet: Understanding the Amazon from Space