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SATELLITE IMAGE PROCESSING IN INDETIFYING OF DEFORESTATION OR SALTY LANDS BY USING AI

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Annotatsiya. Landslides are among the most dangerous and complicated natural hazards, resulting in severe destruction, natural resource damage, and human life and property Landslides usually occur in different types, frequencies, and intensities worldwide. Satellite image processing is a powerful tool that can be used to identify deforestation and salty lands. By using AI, we can analyze satellite images to detect changes in vegetation cover, which can indicate deforestation. Additionally, we can use satellite data to identify areas of high salinity in soil, which can help farmers optimize their irrigation practices.

Key words: launch technology, Planet Labs, Kaggle, satellite, applications, model, precision.

Enter.

Forests play a pivotal role in the global environment and economy. From carbon sequestration to supporting biodiversity and providing livelihoods for millions, their importance is undeniable. However, the world's forests are under threat, with large swathes disappearing each year due to deforestation. To combat this, professionals globally are turning to satellite technology. Through the eyes of these satellites, we gain a comprehensive view of forest cover changes, allowing for timely detection and intervention. This article delves into the intricacies of satellite-based forest monitoring, exploring the technologies, techniques, and applications in the fight against deforestation.

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Home to more than 80% of terrestrial species , forests are reservoirs of biological diversity. From the smallest insect to the largest mammals, they provide habitats that are essential for the survival of countless species.

Satellite image processing is a powerful tool that can be used to identify deforestation and salty lands. By using AI, we can analyze satellite images to detect changes in vegetation cover, which can indicate deforestation. Additionally, we can use satellite data to identify areas of high salinity in soil, which can help farmers optimize their irrigation practices.

Deforestation is a global environmental problem in the 21st century. In recent times, we have seen an explosion of satellite imagery and remote sensing data thanks to improvements in launch technology and low-cost satellites. For the first time ever, we have the capability to combine low-cost satellite imagery and deep learning technologies to tackle these global environmental concerns. In this article I will walk through the steps I took to analyse and categorise a large volume of satellite images from Planet Labs. The objective is to training a deep learning algorithm to automatically categorise the key features in each image. In this way, we can automatically look through thousands upon thousands of satellite images in timely manner and identify illegally logging activities as they occur.

Planet Labs is an Earth imaging company that designs and manufactures miniature satellites. The dataset that we've obtained can be found on Kaggle, and consists of an image of the Amazon rainforest broken down into thousands of chips, each chip is 256 x 256 pixels. Planet's high resolution monitoring product is able to obtain new images on a daily basis, so analysing these images at high speeds will be critical.

The task at hand is to detect the presence of 16 labels in these image chips. The labels are agriculture, bare ground, blooming, blow down, clear sky, haze, partly cloudy, conventional mining, cultivation, habitation, primary rainforest, roads, selective logging, slash burn, water, cloudy skies, and artisanal mining. This is essentially a multi-label image classification problem, where each image can contain one of more of the above mentioned labels. Here are some samples of what our training images look like.

The main part.

Forests play a pivotal role in the water cycle. Through a process called transpiration, trees release water vapor into the atmosphere, influencing rainfall patterns and freshwater availability in many regions. The interwoven relationship between forests and life on Earth underscores their immense value. Protecting them is not just an environmental imperative but also a requisite for socioeconomic stability and biodiversity conservation.

Approximately 1.6 billion people, including many indigenous communities, rely on forests for their livelihoods. Forests offer resources such as timber, medicinal plants, and food, playing a direct role in the socioeconomic well-being of a significant portion of the world's population.

Deforestation, the large-scale removal or degradation of forests, is an urgent global crisis. The consequences are manifold, affecting both our environment and societies in profound ways. Each year, an estimated 10 million hectares of forest are lost, roughly the size of Iceland. While some of this loss is offset by forest growth and replanting, the net annual decrease in forest area over the past decade is approximately 4.7 million hectares. The consequences of such significant forest loss include:

Carbon emissions: Forests act as carbon sinks, storing large amounts of carbon dioxide. When forests are cleared, especially through burning, they release this stored carbon, contributing to global greenhouse gas emissions.

Biodiversity loss: Deforestation threatens the habitats of countless species, leading to reductions in biodiversity. Many species, especially those endemic to specific forest regions, face the risk of extinction.

Soil degradation: Forests maintain soil health by preventing erosion, enriching the soil with organic matter, and regulating water flow. Their removal can lead to diminished soil fertility and increased vulnerability to natural disasters.

Societal implications: Many communities, particularly indigenous populations, depend directly on forests. Deforestation disrupts their way of life, often leading to conflicts over land and resources.

Many regions around the world are facing large-scale deforestation. The Amazon, often referred to as the "lungs of the Earth", has seen alarming rates of forest loss, primarily for cattle ranching and agriculture. Regions in Southeast Asia, such as Borneo and Sumatra, are witnessing rapid deforestation due to the expansion of palm oil plantations. And the Congo Basin, the world's second-largest tropical forest located in Central Africa, faces threats from logging, mining, and the bushmeat trade. The gravity of the deforestation crisis necessitates a concerted global response.

The application of modern technologies, like satellite-based monitoring, offers promise in addressing and mitigating these challenges.
The vastness of global forests poses a challenge for monitoring on the ground. This is where satellite technology comes to the fore, offering a comprehensive, timely, and efficient means to keep tabs on forest cover changes. There are several types of satellite sensors that are used for detecting deforestation:

Optical sensors: These capture images in visible light, much like a standard camera, but can also detect non-visible wavelengths, enabling them to monitor vegetation health and moisture content.

Radar sensors: Using radio waves, radar sensors can penetrate clouds and even capture data at night. They're particularly useful in regions with frequent cloud cover or in assessing structural characteristics of forests.

Thermal sensors: Detecting radiation in the infrared spectrum, these sensors are instrumental in identifying forest fires and areas of heat stress in forests.

One of the key advantages of satellite monitoring is the ability to capture sequences of images over time, which is also known as time-series data. Such data facilitates tracking of gradual changes in forest cover and helps distinguish between temporary shifts (like seasonal changes) and permanent ones (such as deforestation). Furthermore, satellites can often distinguish the cause of forest cover change. For instance, the clear-cut patterns of logging differ from the more scattered, irregular patterns of shifting cultivation. Similarly, the aftermath of natural disturbances, like hurricanes or pest infestations, can also be discerned. Leveraging these capabilities, satellites provide invaluable insights into the state of our forests. Their data, when processed and analyzed, forms the backbone of many forest conservation strategies and initiatives around the world.

The features of the object identified by the CNN are extremely complex because of the number of filters used to identify various patterns. This allows us to identify areas of deforestation or changes in vegetation cover with high precision.

By analyzing satellite images, we can identify areas where salt accumulation is high, allowing farmers to adjust their irrigation practices accordingly.

Convolutional neural networks (CNNs) are known to be very effective with image classification tasks, and that will be our focus here. We will use a bunch of open-cv and scikit-learn Python packages to do our image preprocessing. Then we will use the Keras package together with Tensorflow backend to build convolutional neural networks.

Firstly, we convert our training images into tensors, basically an image can be represented by a bunch of pixel values, and since we're dealing with coloured images, each pixel has 3 channels (RGB). We need normalised pixel values so we divide each pixel value by 255. Our convolutional neural network that we build from scratch has 3 Convolutional 2D layers, each one will use a rectified linear unit as the activation function. We are also going to use a 3x3 convolutional window (the kernel size) and doubling the amount of filters as the network gets deeper. In between our convolutional layers we will use a max pooling layer which will reduce our parameters by a half. Finally the output layer is a dense layer that will match up with our 16 output classes, and the sigmoid activation function will be used. Overall this neural network is quite simple, and serves as a good benchmark for this task.

The imagnet competition has allowed worldwide researchers to come up with state-of-the-art architectures for convolutional neural networks specifically applied to the task of image classification. A very popular technique is to simply use one of these trained state-of-the-art CNN architectures and adapt it to our problem domain (since our problem domain is very similar to the imagenet competition).

These pre-trained CNN architectures are made available within the Keras package and we will pick the ResNet50 model. These CNNs are trained on the imagenet dataset to recognise 1000 everyday object categories. The earlier layers of these CNN networks would also be very applicable to our problem, namely they simply detect edges and shapes. We could simply transfer the learnings from these CNNs onto our problem. The way we do that is to take the ResNet50 model, and unfreeze the weights of the latter layers while freezing the weight of the initial layers. We replace the output layer of the ResNet50 model and adapt it to our problem by adding a dense layer with 16 output classes (instead of 1000!).

Our transfer learning model took around 8 hours to train on a GPU! But we have improved on our results. We achieved a recall score of 0.83, a precision score of 0.89 and a F-beta score of 0.84. Our F-beta score, which is a measure of both recall and precision, assigns a greater value towards recall since we want to detect all labels that are present in these images, as oppose to how precise these classifications are. We also produced some useful visualisation here to ensure that our model isn't overfitting. The graphs below show that both accuracy and loss are headed in the right direction given our number of training epochs.

Satellites capture data across multiple wavelengths, some beyond human vision. Spectral analysis involves examining these different wavelengths to identify specific materials on the ground. For example, healthy vegetation reflects light differently from stressed or dead vegetation. By analyzing these spectral signatures, scientists can assess forest health and detect early signs of degradation.

Modern computing brings the power of machine learning to satellite data analysis. Algorithms can be trained to recognize patterns associated with deforestation, such as the layout of roads leading to logging areas or the distinctive shapes of clear-cuts. Once trained, these models can rapidly scan vast areas, pinpointing potential sites of deforestation with high accuracy.

Often, a holistic understanding of forest health requires integrating data from multiple sources. This can include combining optical, radar, and thermal satellite data or integrating satellite imagery with ground-based observations. Such fusion provides a more comprehensive view of forests, improving the accuracy of deforestation assessments.

This involves comparing satellite images taken at different times to identify changes in land cover. By overlaying and analyzing images from different periods, researchers can detect and quantify forest loss, distinguishing it from other land cover changes like seasonal vegetation shifts.

In recent years, the Brazilian government and NGOs have employed the use of satellites to track deforestation in the vast expanse of the Amazon. Through near real-time monitoring, authorities have been able to swiftly identify illegal logging activities and deploy enforcement teams on the ground. The system, known as (Real-Time Deforestation Detection System), has been instrumental in curbing illicit deforestation in certain parts of the Amazon.

With the rapid expansion of palm oil plantations threatening biodiverse-rich forests, conservationists have harnessed satellite data to monitor land use changes. The ability to detect newly constructed roads, a precursor to logging and plantation activities, has allowed early interventions and advocacy efforts targeting specific companies or supply chains.

The resolution of satellite imagery varies. While high-resolution imagery can provide detailed insights, such data may not always be available for all regions or may be expensive to procure. On the other hand, lower-resolution imagery, while covering larger areas, might miss small-scale deforestation activities.

For a comprehensive understanding, satellite data often needs to be integrated with on-ground observations. However, in remote or conflict-prone regions, collecting ground data can be challenging, leaving potential gaps in the overall monitoring effort.

Satellites of the future will offer even higher resolution imagery, allowing for detailed analyses of smaller patches of forest. This enhancement will enable conservationists to detect minor changes and disturbances, further improving the accuracy of monitoring efforts.

Advances in radar and LiDAR technology will allow satellites to better penetrate cloud cover. This will be especially valuable for continuously monitoring cloud-prone regions like the Amazon and Southeast Asian rainforests.

The integration of AI and machine learning will become even more sophisticated, enabling real-time processing of satellite imagery. This means potential deforestation events could be flagged almost immediately after they start, allowing for rapid response.

Summary. In conclusion, satellite image processing is a powerful tool that can be used to identify deforestation and salty lands. By using AI, we can analyze satellite images to detect changes in vegetation cover and identify areas of high salinity in soil. These applications have the potential to help us better understand and manage our environment.

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