PROJECT PLAN

DETECTION OF VOLCANIC PLUMES USING TRANSFER LEARNING

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Introduction

Volcanic eruptions have caused significant changes in life's evolution and global extinctions(Auker et al. 2013), and early detection of volcanic plumes is crucial for effective risk management(Poland 2015). Volcanic activity is always accompanied by releasing SO_2 (Sulfur Dioxide) into the atmosphere as part of volcanic plumes. The amount of SO_2 emitted during an eruption can vary greatly depending on the type and intensity of the eruption. Explosive eruptions, which involve the rapid release of magma and gas, tend to produce larger amounts of SO_2 than effusive eruptions, which involve the slow flow of magma(Carn et al. 2017). SO_2 concentrations can be measured from space using satellites and its measurement is a very useful tool for detecting volcanic activity on a global scale(Nowlan et al. 2011). However, the explosion in satellite data has brought major challenges associated with manual inspection of imagery and timely monitoring(Fernández et al. 2017). Especially for globally volcanic detection, it requires a significant amount of manual effort to identify plumes in traditional detection methods(Sun et al. 2020). Hence, the motive of this project is to develop an automated transfer learning-based approach for detecting global volcanic activities and identifying volcanic plume types. Several pre-trained methods that use existing models will be compared to determine which one performs the best.

The main contribution of this project can be summarized in the following:

1. To provide a framework based on deep learning architecture for the detection and classification of volcanic plume and global volcanic activity.
2. To analyze the concept of transfer learning on four different deep learning architectures.
3. To provide a comparative analysis of each deep learning architecture with respect to accuracy in the context of transfer learning.

Related Works

2.1 Satellite technique and data problem

Satellite sensors have been widely used for volcanic activity monitoring tasks, eg. (Nikita Markovich Fedkin et al. 2020) introduced a machine learning based algorithm for fast retrievals of effective volcanic SO_2 layer height (SO_2 LH) from the Ozone Monitoring Instrument (OMI), which can also be readily adapted for other satellite UV-Vis spectrometers. However, the problem of deformation signals from atmospheric artifacts(Anantrasirichai et al. 2018) and a within-class imbalance of volcanic data(Anantrasirichai et al. 2019) would strongly affect training r esults. Data augmentation, interferogram reduction(Anantrasirichai et al. 2018), and synthetic data generation(Anantrasirichai et al. 2019) were used for volcanic data pre-processing.

2.2 Transfer learning and object detection

Machine learning algorithm typically requires a large amount of data to be trained from scratch. However, it can be challenging to obtain a sufficiently large dataset that is relevant to the problem being addressed in certain cases. Thus, transfer learning was introduced to handle the situation of fewer labeled data. By leveraging the knowledge gained from training on a large dataset, the pre-trained model can be fine-tuned for a new task with a smaller dataset(Weiss, Khoshgoftaar, and Wang 2016). This technique has proven to be effective especially in image classification and object detection. It has been applied in different domains, e g. rice plant diseases detection(Chen et al. 2020), breast cancer detection(Khan et al. 2019), airplane detection(Chen, Zhang, and Ouyang 2018), detection of COVID-19 infection(Das et al. 2022) etc.

Using GoogLeNet(Szegedy et al. 2015), Visual Geometry Group Network(Simonyan and Zisserman 2014), and Residual Networks(He et al. 2016) pre-trained on the ImageNet dataset as a feature extractor for classification is a typical way to apply transfer learning techniques(Khan et al. 2019).

Methodology

3.1 Data

In this project, we are going to use TROPOMI SO_2 data from the Sentinel-5P (S5P) satellite to monitor and detect volcanic SO_2 gas plumes. The TROPOMI imaging spectrometer on-board the Sentinel-5P satellite was launched in 2017 and has been providing data since December 2018. It offers high-quality data with a revisit frequency of 1 day and allows for the detection of volcanic SO_2 with unprecedented precision(Theys et al. 2019).

3.2 Technical routes

As shown in Fig 1, our project will be mainly divided into three steps: 1. Data collecting and pre-processing; 2. Pre-trained CNN architecture for feature extraction 3. Transfer learning and validation.

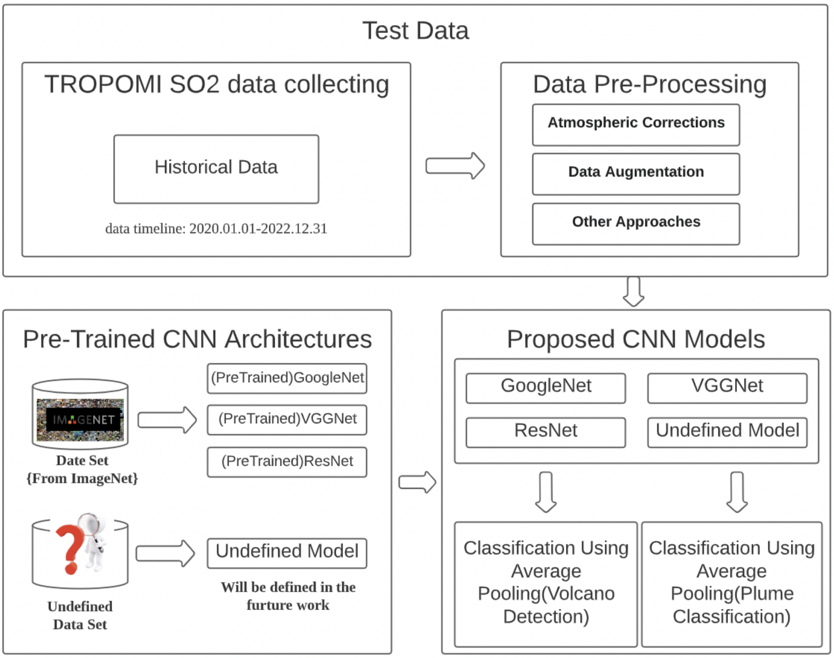

Figure 1. Block Diagram of the Proposed Deep Learning Framework

Main Challenges

The first challenge arises from the data. Signals of ground targets obtained through sensors does not always reflect the true surface reflectance, as atmospheric absorption and scattering can cause errors in the radiation measurements. These atmospheric artifacts can also generate concentric fringes around volcanoes, particularly those with steep topography(Pinel, Poland, and Hooper 2014). Thus, we have to discuss and decide whether to use atmospheric corrections to improve model accuracy. In addition, noise exists in the data, which can be identified and affect the results. Therefore, in the preprocessing stage, we need to discuss whether other techniques are needed to remove the noise.

We also need to decide how many volcanoes around the world to monitor, as this is related to the amount of manual labeling work required. In some articles, they detected more than 900 volcanoes worldwide(Anantrasirichai et al. 2018), while in MODIS they monitored more than 200 volcanoes globally(Wright et al. 2002).

Another challenge is to find a new dataset for pre-training that is different from the existing database (ImageNet). We need to observe whether this new dataset has improved the overall performance of the model compared to other models.

Last but not the least, combining geographic expertise knowledge with experimental results and seeking broader applications can be challenging. For example, variations in the altitude of an SO_2 plume affect the amount of photons that are backscattered through the layer(Nikita M Fedkin et al. 2021). What if we combine the detection result with SO_2 altitude.

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