Deep Learning-based Approach to Prediction of Volcanic Fallut Spread

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Abstract

The volcaninc fallout ash is one of the major causes making the volcanic eruption a fatal natural disaster. The spread of volcanic fallout is predicted by complex calculation which requires huge computing resources to make accurate prediction, and to get prediction result more faster, the preivious researches focused on making lighter simulation model (9), standardizing the variables used to simulate the spread (12), and increasing the efficiency of utilizing the simulated prediction and other informatino from different sources (10). Still, the needs for the complicated calculation last, therefore, our research wants to suggest a faster solution on predicting the volcanic fallout spread utilizing the state-of-the-arts deep learning model.

1 Introduction

The volcanic eruption is one of the most severe natural disasters which occasionally happens. However, comparing to the other disasters which can be predicted, like typhoons and storms, predicting the exact time and scale of volcanic eruption considered as a very difficult task, which might never be accurate, according to Einarsson (as cited in 3, para.7 & 30). Though there exist various ways that volcanic eruption to cause countless casualties and massive economic loss, according to Yun (13, p.274), the fallout ash, the focus of this research, considered as one of the most significant by-products making deadly effects. Including the respiratory damage of lives, threatening the safety and reliability of air transportation, and the collapse of structures

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caused by sedimentation of the ash, the fallout ash causes various impairments in a wide range of areas (13, p.274-275).

To mitigate the hazardous effects caused by the fallout ash, it is important to properly predict the direction of ash spread and alert citizens who reside through the path of the ash dispersion. Historically, by using the Eulerian or the Lagrangian approach, according to Bonadonna et al. (2, p.3-4), scientists tried to make Volcanic Ash and Dispersion/Tracking Model (VATDM). These models usually focused on predicting the pathway of fallout ash dispersion and the amount of deposited ash while accepting limited variables (13, p.276).

However, these models' predictability might be limited due to computing performance (11, p.745-746), as the model needs to calculate the movement of all particles that want to predict. To be more specific, the number of particles to be tracked by VATDM and the calculation requirement have positive relationship; Scollo et al. (8) confirmed that it required up to hundreds of millions of particles to get accurate simulation result, meaning that the simulation with small number of particles might not able to illustrate the region of disperse accurately.

To make a faster prediction, researchers studied on making a lighter and faster prediction model (9), standardizing the eruption parameters required to run the model ((12, p.7)), and figuring out the way to store and retrieve different kinds of data (satellite and prediction from the mathematical model), which needed when deciding the final prediction result, more efficiently (10). Though the advance of the models and simulated results' utilization efficiency has been improved with the effort of numerous scholars, still the needs of the calculation process last, which yet limiting the ability of prediction to the computing power.

In this research, we are going to suggest a faster way to get the prediction on the pathway and area that might be affected by volcanic fallout ash: deep learning. By utilizing the state-of-the-arts deep learning architectures, our goal includes verifying whether deep learning can predict the spread of fallout ash. (See **Figure 1** for the model's structure)

To be more specific, we are going to construct a model based on the conditional Generative Adversarial Network (cGAN), proposed by Isola et al. (4),which focused on translating one image to the other type of image (Image-to-Image Translation). Comparing to the previous work (4), while the previous architecture only got an image as an input and produced one output image, our deep learning model should get several images and need to produce

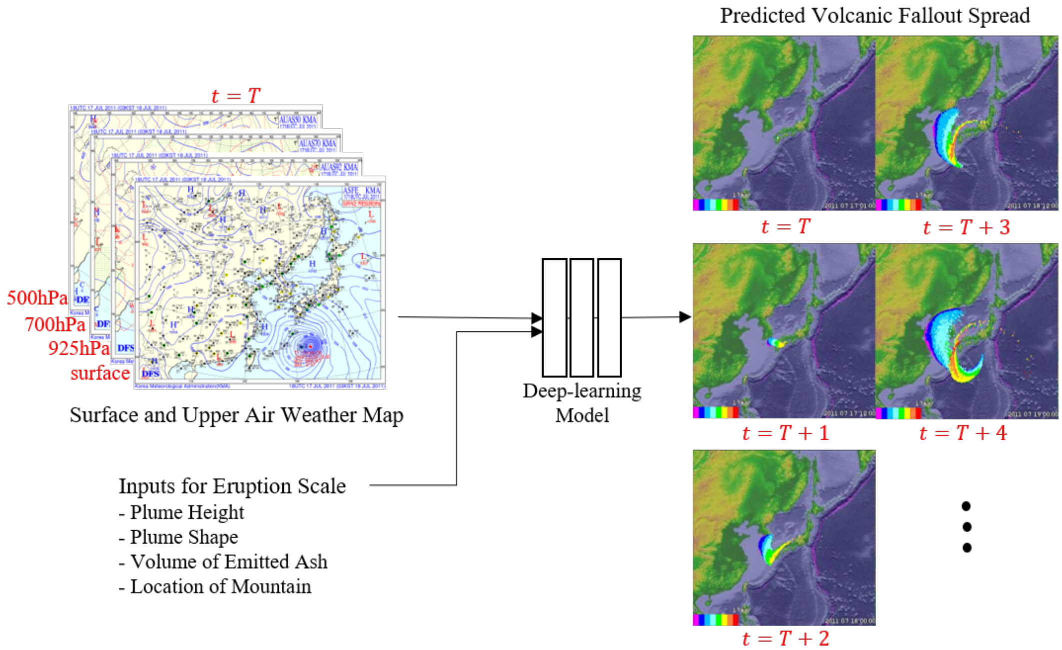

Figure 1: Overview of the Research Goal This research aim to make a deep-learning model which predicts volcaninc fallout spread while getting the weather maps (both surface and upper air) and eruption scale parameters (Plume height, Plume shape, Volume of Emitted Ash, and the location of mountain) as an input.

continous images to represent the direction and speed of ash spread. The details regarding the model structure are writen below (Method - Model structure).

2 Methods

Data Collection To achieve our goal, making a generator which predicts the possible area of ash spread for the given weather conditions and eruption scale, we first need to collect input and output data pairs. To collect these, for the input images, we will download those from the "Meteorological Data Open Portal" operated by the Korea Meteorological Administration (KMA) (from MDO). To get the output data, we will go through the traditional procedure (simulation with VATDM).

The simulation parameters except for the weather data will be set manually. To represent various eruption cases, for each mountain to be used as the sample, we will simulate with the constants representing Volcanic Explosivity Index (VEI) 3 (Moderate Large Eruption), VEI 5 (Very Large Eruption), and VEI 7 (Massive Explosive Eruption) (6, p.1232). The weather prediction data, will be obtained by the same location where we found the weather maps: download prediction made by RDAPS(regional data assimilation and prediction system) (from MDO).

Model structure We decide to use conditional GAN-based model, which has been shown to have good performance on generating indistinguishable images compare to the *real* images (4). The GAN has two distinctive parts of functions - Generator and Discriminator - and we need to fit both function simultaneously. The goal for the Discriminator is to check whether the generated image is fake or not, while the Generator's goal is to make image, which enough to make the Discriminator to categorize it to a *real* image. While the original GAN only uses a random noize to generate the output, the conditional GAN not only gets random noize but also gets the *condition* vectors as an input. For our model, the condition vector contains information of the weather maps and the eruption scale.

Comparing our model with Isola et al.(4)'s cGAN model, whlie Isola et al. provided only one image as an input, we have to pass not only the several weather map images but also the numerical vector indicating the eruption scale of the volcano. Moreover, while Isola et al.(4) challenged to provide randomness to their output, we want our model to provide same output when the same inputs have been provided. Lastly, our model needs to provide continuous images to represent the dispersion of volcaninc ash overtime, however, the Isola et al.(4)'s model only need to provide a still photograph as an output.

To contruct the model, we will use U-Net architecture, proposed by proposed by Ronneberger et al. (7), for the convolutions to pass the information on the weather maps to the neural network. As U-Net architecture has achieved a promising result on several different image tasks(4, 5), we are expecting that this architecture also works for our task. However, we still have to come up with a solution to pass information from several different images and one numerical vector to our neural network when we train our model. After that, we are going to choose proper loss functions that make the best result on predicting the relationship between elements depicted on the weather maps to the spread of the ash.

Model Analysis and Experiments While we mauver over various loss functions, we are going to make various models utilizing different loss functions and compare those with the quantitative metric. As indicated in the previous paper (4), it is difficult to say there exists one best representation of the quality of translated images. Therefore, we need to set reliable measurements before we analyze models using different loss functions.

Table 1: Detailed Timeline

Due date	Task description
Mar. 14	Select proper VATDM to generate training/testing sets
Mar. 20	Collect weather maps and weather prediction data
Apr. 10	Run simulation and collect outputs
Apr. 31	Choose candidates for final model's structure
Jun. 15	Conduct and analyze experiments on each nodels
Jul. 15	Write reports

Once we decide the model structure, we need to verify the amount of sufficient size of training datasets so that it can translate the weather map images to simulation results flawlessly. To do these tasks, we need to train models with different amounts of inputs. As the Korean Peninsula experiencing four distinctive seasons, while we picking up the training set randomly, we would better ensure that we pick a combination of data that represents the dynamic climate of Korea. After we fit the model with a different number of training datasets, we will investigate how well each model draws the result.

3 Timeline

The first thing we should do is to get the input. As there is no available API to get the weather maps and data from KMA, but they provide an interactive website to download the data, it might take some time to get all data manually. Moreover, the calculation time for that simulation was not ignorable, according to a previous experiment (it takes approximately one hour to get one output with the laptop having Intel's i5-3320M CPU). Considering the factor that we have access to better computing power than the previous test, we are expecting to finish data collection within two months after the project initiated.

The next step is to train the generator with a given input-output pair. To fit the conditional GAN based model and to verify the result with various test cases, we are expecting to take two additional months here. For the last month of this research, we will write a report and posters.

The detailed timeline is on the **Table 1**.

4 Conclusion and Future Direction

We are expected to make a deep neural network model to predict possible pathway and area of volcanic fallout ash spread faster than the previous methods, by using simpler and lighter input, weather maps, compare to the weather dataset predicted by RDAPS. Not only reduce the computing time to predict the spread, but the model aims to reproduce as the same result as possible compares to the original training result. To verify our idea and model structure, we utilize weather maps representing the weather conditions and volcanos near the Korean Peninsula.

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