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 information from different sources [10]. Since the needs for the complicated calculation still present, our research suggests 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]. Although the volcanic eruptions cause countless casualties and massive economic loss in various ways, according to Yun [13, p.274], the fallout ash is considered as one of the most significant by-products causing deadly effects. Resulting in the respiratory damage of lives, threatening the safety and reliability of air transportation, and the collapse of structures 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 in the affected area. Historically, according to Bonadonna et al. [2, p.3-4], scientists tried to make Volcanic Ash and Dispersion/Tracking Model (VATDM) by using the Eulerian or the Lagrangian approach. These models usually focused on

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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 the computing performance [11, p.745-746], as the model needs to calculate the movement of all particles that need to be predicted. To be more specific, there is a positive relationship between the number of particles to be tracked by VATDM and the calculation requirement. 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 be 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), needed when deciding the final prediction result more efficiently [10]. Though the models themselves and utilization efficiency of simulated results have been improved with the effort of numerous scholars, still the needs for the calculation process remain, which yet limit the ability of prediction by 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 continous images representing the prediction of the direction and speed of the 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 both surface and upper air weather maps from the "Meteorological Data Open Portal" operated by the Korea Meteorological Administration (KMA) [MDO]. To get the output images, we will go through the traditional procedure (simulating by VATDM).

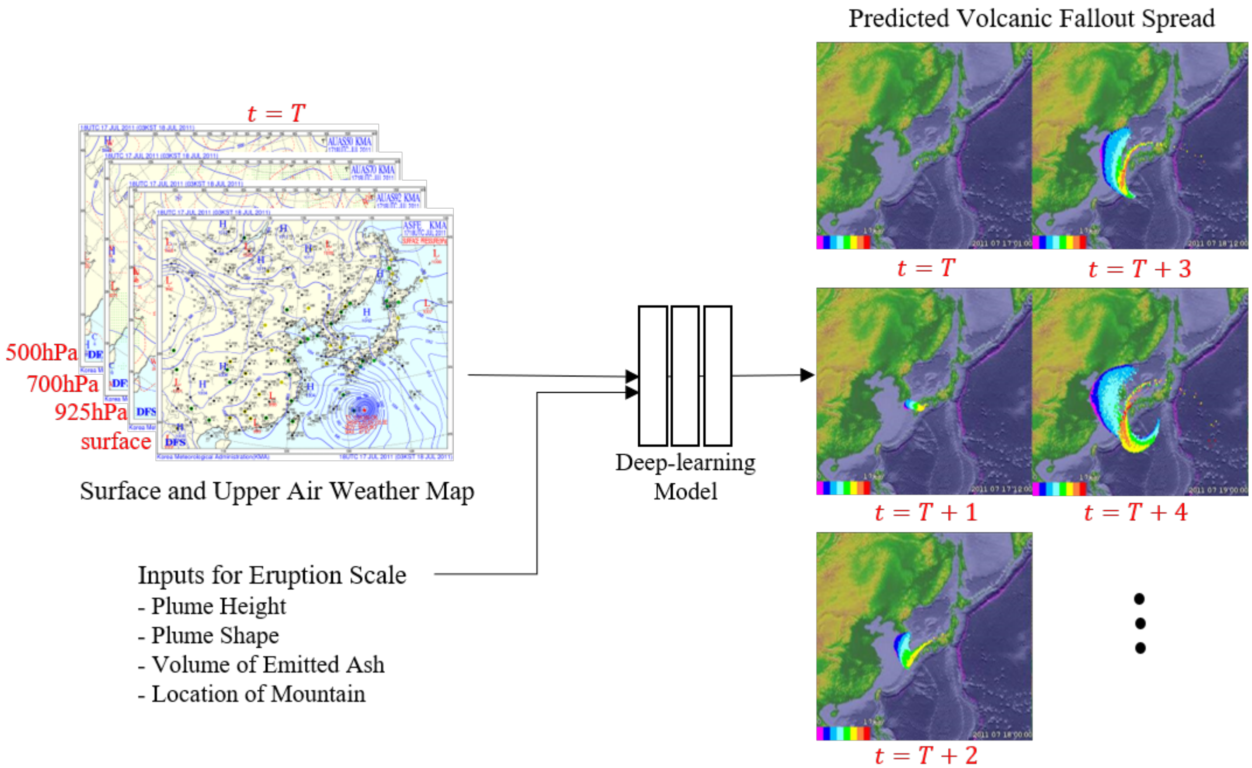

Figure 1: Overview of the Research Goal This research aims to make a deep-learning model which predicts volcaninc fallout spread while accepting the weather maps (both surface and upper air) and eruption scale parameters (Plume height, Plume shape, Volume of Emitted Ash, and the location of mountain)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

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) [MDO]. 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].

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 is enough to make the Discriminator to categorize it as a *real* image. While the original GAN only uses a random noize to generate the output, the conditional GAN gets not only random noize but also 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 the several weather map images and the numerical vector indicating the eruption scale of the volcano. Moreover, while Isola et al.[4] challenged to provide randomness to the output, we want our model to provide the identical 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 needed to generate a still photograph.

To contruct the model, we will use the U-Net architecture, proposed by Ronneberger et al. [7], for the convolutions to pass the information on the weather maps to the neural network. As the U-Net architecture has achieved promising results on several different image tasks[4, 5], we expect that this architecture will also work 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 manuver 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 that 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.

Once we decide the model structure, we need to determine the amount 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. While we select training sets randomly, we should ensure that we pick a combination of data that represent the dynamic climate of Korea as it experiences four distinctive seasons. 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. There is no available API to get the weather maps and data from KMA. Therefore, we must use the interactive website provided by KMA to download the data; this is expected to take some time. Moreover, the calculation time for that simulation was not ignorable, according to a previous experiment (it takes approximately one hour to get one output through a laptop with Intel's i5-3320M CPU). Considering that we have access to better computing power than the previous test, we expect to finish data collection within two months after the project's initiation.

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

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

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

4 Conclusion and Future Direction

We expect to make a deep neural network model to predict possible pathways and areas where volcanic fallout ash spreads faster than the previous methods by using simpler and lighter input, the weather maps. Not only does the model reduce the computing time to predict the spread, but the model also aims to reproduce results as similar as possible compared to the original training result. To verify our idea and model structure, we utilize weather maps representing the weather conditions and volcanos around the Korean Peninsula.

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