Can Eruptions Be Predicted? Short-Term Prediction of Volcanic Eruptions via Attention-Based Long Short-Term Memory

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Abstract

Short-term prediction of volcanic eruptions is one of the ultimate objectives of volcanology. At Sakurajima volcano, an active volcano in Japan, experts monitor the volcanic sensor data and analyze the prior signal to predict the eruptions. Even though experts derived some patterns, it is hard to make a good prediction due to handcrafted features. To address this issue, we propose to predict eruptions using machine learning. In this paper, we attempt to predict the eruptions hourly by adapting several machine learning methods including traditional and deep learning approaches. As recurrent neural network is well-known for extracting the time-sensitive features, we propose the model especially for volcanic eruption prediction named VepNet. The assumption is based on domain knowledge that some specific triggers are the main causes of future eruptions. To take this advantage, VepNet deploys an attention layer to locate and prioritize these triggers in decision making. The extensive experiments ever conducted using data from Sakurajima volcano showed the effectiveness of deep learning approach over the traditional approach. On top of that, VepNet showed its effectiveness on prediction with AUC-score up to 0.8665. Moreover, an attempt has been made to explain the mechanism of the eruptions by analyzing the attention layer of VepNet. Lastly, to support volcano expert in issuing warnings and the safety of living people around Sakurajima, a warning system named 3LWS is proposed. The system predicted the eruptions hourly with high accuracy and reliability with the eruption rate up to 68.97% in the High-Risk level.

Introduction

Volcanic eruptions cause severe damages to human and society, hence it is an important research topic to solve. In the context of this paper, the eruption means explosive eruption. Volcano experts at Sakurajima volcano deploy a monitoring system (Figure 1) which includes the sensors to measure time series data like strain and energy data (Iguchi et al. 2013). The details of these data will be explained later in the Background Knowledge and Dataset section. Experts observe the data over many years to extract the prior signals of these data before an eruption occurs and found some interesting patterns (Kamo and Ishihara 1989; Iguchi et al. 2008). However, it is hard to map that knowledge into an accurate model due to handcrafted features. This creates an opportunity for machine learning researchers to solve this problem while collaborating with volcano experts.

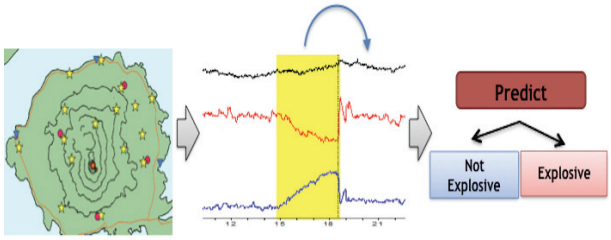

Figure 1: The monitoring system and short-term prediction at Sakurajima volcano.

In this paper, we attempt to predict the eruptions hourly using the historical sensor data two hours ago. This setting is due to domain knowledge and recommended by volcano experts. An eruption is very hard to predict more than an hour in advance due to the limitation of the current technology (Sparks 2003). The factors that lead to a volcanic eruption unfold deep inside our planet, further down than current technology can reach. In the current monitoring system, the prior signals of an eruption measured by the sensors on the ground are clear only when the eruption is about to happen soon. That is why in this paper, we predict the eruptions an hour in advance and use the past data of two hours ago as more data just increase the computational cost and do not bring much useful information about the eruptions. The prediction will be made hourly and is either *explosive* or *not explosive*.

We conduct this research on two perspectives: traditional and deep learning approaches. As recurrent neural network is promising for learning the nonlinearity and the temporality of time series data, we propose a modern deep neural network architecture called Volcanic eruption prediction (VepNet) especially for the short-term prediction of vol-

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canic eruptions. VepNet employs a stack of two Long Short-Term Memory (LSTM) to extract the high level and time-dependent features from the sensor data. As each LSTM cell can handle multiple data points at one time step, the model can handle multivariate time series data easily. This is important because the eruptions can be predicted more accurate if we give more data to the model from different sources. On top of LSTM, VepNet employs a concatenation-based attention layer which plays a role as a selector to automatically judge the importance of each time step for the prediction (Luong, Pham, and Manning 2015). Furthermore, we propose a 3-Level Warning System (3LWS) to issue the warning at Sakurajima volcano in real-time.

We have conducted extensive experiments for the short-term prediction of volcanic eruptions on the real and large datasets obtained from Sakurajima volcanic monitoring system. The experimental results show that deep learning approaches, especially VepNet, outperforms traditional models on a large test set with a wide range of evaluation metrics. The following are the main contributions of this paper:

- The research tackles an important problem of short-term prediction of volcanic eruptions on a wide range of machine learning models.
- We propose a modern architecture named VepNet, an end-to-end, powerful and effective model for eruptions prediction with minimum data preprocessing. VepNet not only predicts the eruptions well but also provides a meaningful interpretation of the prediction. To the best of our knowledge, this is the first attempt to adopt deep learning for the challenging research of short-term prediction of volcanic eruptions.
- We propose a 3-Level Warning System (3LWS) for issuing the eruption warnings in real-time. The proposed system achieved high accuracy and reliability. 3LWS supports volcano experts in the decision of issuing warnings. This could bring a strong impact on society.

Related Work

There are limited works on the short-term prediction of volcanic eruptions. Most of the prediction works are done by volcano experts using their own experience by monitoring data through time, which is hard to make a fast and accurate prediction. Some of the popular data volcano experts use for prediction are seismicity, ground deformation, and volcanic gases (Sparks 2003). (Chouet et al. 1994) predicted the explosive eruptions at Mount Redoubt, Alaska using seismic data. The Alaska Volcano Observatory issued warnings of several eruptions based on changes in seismic activity related to the occurrence of precursory swarms of long-period seismic events. The ground deformation and seismicity are used together to forecast the Hekla eruption (Agustsson et al. 2000). Its seismic expressions were a swarm of numerous small earthquakes related to its onset. A swarm of small earthquakes was observed some 80min before the onset of the eruption. At the same time, a compressive strain signal was observed at strain station 15 km from Hekla. The integration of precursory seismicity, ground deformation, and SO_2 emissions led to a successful forecast at Mount Pinatubo (Newhall and Punongbayan 1996). (Kamo and Ishihara 1989) categorized the volcano's status into multiple warning levels based on the thresholds of the inflationary tilt, the deflationary tilt, and the accumulated values of these data over time. The shared point of these works is that the prediction mainly relies on the knowledge of the volcano experts, which requires a lot of domain knowledge and the difficulty of discovering complicated patterns. Moreover, as each volcano has its eruption characteristics, the prediction knowledge from one volcano is hardly used in the other volcanoes. Therefore, the generalizability is low. Our approach has better generalizability as the model only needs to be retrained for each volcano.

Background Knowledge and Dataset

Sakurajima is an active volcano located in Kagoshima Prefecture in Kyushu, Japan [1]. Many explosive eruptions are occurring in this volcano every week. Strain data and seismic data are the two main monitoring data at this volcano. Strain data (including tangential strain data and radial strain data) is measured by Strainmeters. These instruments measure linear strain by detecting horizontal contraction or extension in a length. The component installed in the direction of the crater (radial component) measures radial strain. The component installed perpendicular to the radial direction (tangential component) measures tangential strain. Seismic data (including seismic energy data and maximum amplitude data) is measured by Seismometer. This measures ground surface vibration as the velocity of a particle. The square sum of the velocity is proportional to seismic energy data to evaluate the intensity of long-term tremor. Maximum amplitude velocity in the seismic records is treated as the instantaneous intensity of the event. The visualization of the data is shown in Figure 2.

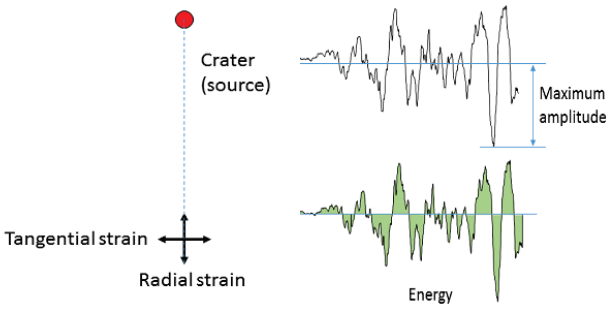

Figure 2: The visualization of strain data (left) and seismic data (right).

The data for all sensors are numeric values and recorded every minute by volcano experts. The total data includes eight years from 2009 to 2016, and this is the biggest dataset about the volcanic monitor in Japan. We use the sliding window of two hours and the sliding step of one hour to segment the sensor data. The two labels *explosive* and *not explosive* are carefully done by volcano experts. The details

[1] https://en.wikipedia.org/wiki/Sakurajima

of the dataset are shown in Table 1. We merge the dataset from 2009 to 2012 because it is used together for training. We can see that the class imbalanced problem is severe in this dataset.

Table 1: The details of the dataset for short-term prediction of volcanic eruptions. Abbreviation: Sequences (Seq), Explosive (Exp).

	2009-2012	2013	2014	2015	2016
Seq	34,123	8,420	8,684	8611	8,659
Exp	3,130	742	409	642	47
Exp rate	1:10	1:11	1:21	1:13	1:184

VepNet: Short-Term Prediction of Volcanic Eruptions

Problem definition

The model takes D sensors as the input and each sensor is a time series of length n. Each element x_i^d of the input is the i^{th} element of the time series obtained from sensor d, where $1 \leq i \leq n$ and $1 \leq d \leq D$. In short, we denote x_i as the value of all sensors at time i. Each input has a corresponding output which is the prediction the volcano $y \in \{0, 1\}$ with 0 is *not explosive* and 1 is *explosive*.

Model

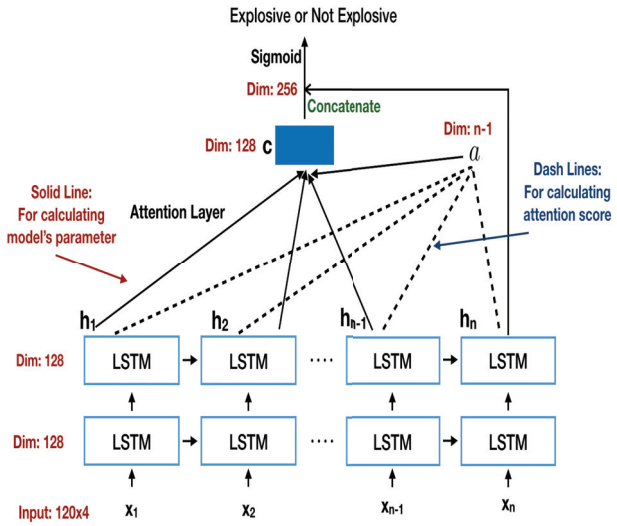

Figure 3: The architecture of the proposed VepNet.

Figure 3 shows the overview architecture of the model. At each time step, the input to LSTM will be x_i which is the value of 4 sensors at time i. The total number of the time step is n which is 120 in our experiment. The input vector x_i is fed into a 2-layer Long Short-Term Memory and outputs hidden state h_i for each time step. The dimension of the hidden state in our experiment is 128. On top of LSTM, VepNet employs an attention layer which takes into account all the hidden states but the last one with weighting vector a. The attention layer outputs a context vector c. The dimension of the context vector c is the same as the hidden state. Finally, the context vector c and the final hidden state h_n will be concatenated to make the prediction using a fully connected layer with a sigmoid function. The details of the model will be explained later in this section.

Long Short-Term Memory (LSTM) LSTM is a type of recurrent neural network which overcomes vanishing gradient problem (Hochreiter and Schmidhuber 1997) by incorporating gating functions into their state dynamics. The output at each time step of LSTM is a hidden vector h which represents the information learned from the time series up to that point. By using the hidden state h of an LSTM as the input to another LSTM, we can stack LSTMs, creating deeper architectures. The hidden state h at layer l obtained from previous layer $l-1$ is

$$h_t^l = lstm(h_t^{l-1}, h_{t-1}^l),$$

with $lstm$ simply represents the gate computation of LSTM, h_t^{l-1} is the hidden state of layer $l-1$, h_{t-1}^l is the hidden state of the layer l at previous time step $t-1$. VepNet consists of a stack of two layers of LSTM to extract the hierarchical level and time-dependent feature representation (Hermans and Schrauwen 2013). The output of VepNet now is hidden vectors $h = [h_1, ..., h_n], h_i \in \mathbb{R}^m$, with m is 128, and h_n is the last hidden state.

Attention Mechanism In the case of volcanic eruption, the trigger of the eruption in the sequence could be anywhere. To deal with this problem, we employ an attention layer on top of LSTM to selectively weighting the hidden states to make the prediction. In this paper, we propose using concatenation-based attention which can relate the correlation between the last hidden state and all other hidden states.

For each hidden state h_i in $[h_1, ..., h_{n-1}]$, we first concatenate h_i with the last hidden state h_n. The attention contribution at time step i is calculated as:

$$a_i = \tanh([h_i; h_n]W_a), W_a \in \mathbb{R}^{2m}$$

The normalized attention contribution vector is:

$$a = Softmax([a_1, a_2, ..., a_{n-1}])$$

The attention is applied up to the second last hidden state. The context vector is derived based on the attention contribution vector a and all the hidden states from h_1 to h_{n-1}:

$$c = \sum_{i=1}^{n-1} a_i h_i$$

Then, the context vector c and the hidden state h_n are combined to generate the attentional hidden state as:

$$h_{attention} = [c; h_n]W_{attention}, W_{attention} \in \mathbb{R}^{2m \times k}$$

with $k = 256$ is the dimensionality of the attentional hidden state.

Short-Term Prediction of Volcanic Eruptions VepNet takes the attentional hidden state from the attention layer to make the prediction using a fully connected network with a sigmoid function:

$$y = Sigmoid(Wh_{attention} + b)$$

with W and b are the weight matrix and bias, respectively.

Optimization We minimize the weighted binary cross-entropy loss function and increase the positive weight to deal with False Negative cases. This is because False Negative cases in volcanic eruption prediction are dangerous.

$$L = -\sum_{i=1}^{batch\_size} y_i \log(y_i') \times weight + (1 - y_i) \log(1 - y_i'),$$

with y is the target and y' is the prediction. The parameter $weight$ with the value of more than 1 is included to the loss function to penalize the cases when the target is 1 but the prediction is near 0. By optimizing the loss function this way, we can force the model to decrease the number of False Negative cases. In our experiment, the $weight$ parameter was decided using the validation set, and the value was set to be 4.

Experiments for Short-Term Prediction of Volcanic Eruptions

Experimental Setup

We do the experiments in several models including traditional and deep learning approaches. Traditional models include 1NN-ED (1NN-DTW was not used due to intractable computational cost which is not appropriate for fast prediction), SVM, and Random Forest (RF). Deep learning models include 4-layer CNN, 2-layer LSTM, and VepNet. Due to the class imbalanced problem, we did not use accuracy to evaluate the models. For a fair and complete evaluation, we used four metrics AUC, F1-score, Precision, and Recall.

Results

All models were tested in four years from 2013 to 2016. For each year, the training set was all the previous years. The result of all models for all four years is shown in Table 2. Deep learning models outperformed the traditional models by a wide margin. This is because the neural networks can learn a better representation of the sensor data. These features can capture the prior signal of the eruptions better. Between deep learning models, LSTM generally performed better than CNN. This is as expected that LSTM can learn the time-sensitive features better than CNN in many applications. VepNet which takes advantages of attention layer resulted in an improvement over pure LSTM model. This can be explained because the eruption can be triggered at any time steps before the eruption. The model which takes advantages of these important time steps can make a better prediction. VepNet performed the best in 2014 with AUC up to 0.8665 and recall of 0.5795. While VepNet can make good predictions from 2013 to 2015, the result was not good in 2016. This is because the class imbalance in 2016 is extremely high. However, the recall of 0.2979 is encouraging as the number of eruptions in this year is very small.

Table 2: The results of VepNet and other models for 4 years. The best model is shown in bold.

	AUC	F1-score	Precision	Recall
2013				
1NN-ED	0.5259	0.1282	0.1552	0.1092
SVM	0.5199	0.0969	0.2061	0.0633
RF	0.5006	0.0053	0.1538	0.0027
CNN	0.8015	0.4022	0.3179	0.5472
LSTM	0.8295	0.4372	0.3722	0.5296
VepNet	**0.8373**	**0.4506**	**0.3773**	**0.5593**
2014				
1NN-ED	0.5251	0.095	0.1	0.0905
SVM	0.5136	0.0611	0.1391	0.0391
RF	0.5014	0.0093	0.1053	0.0049
CNN	0.8375	0.388	0.2942	0.5697
LSTM	0.8484	0.4374	0.354	0.5721
VepNet	**0.8665**	**0.467**	**0.3911**	**0.5795**
2015				
1NN-ED	0.5248	0.1201	0.1218	0.1184
SVM	0.5494	0.1726	0.2807	0.1246
RF	0.5091	0.0409	0.3333	0.0218
CNN	0.7934	0.3965	0.3321	0.4919
LSTM	0.8321	0.38	0.3053	0.5031
VepNet	**0.838**	**0.4125**	**0.3445**	**0.514**
2016				
1NN-ED	0.5113	0.0182	0.0116	0.0426
SVM	0.499	0.0	0.0	0.0
RF	0.4999	0.0	0.0	0.0
CNN	0.7282	0.0965	0.0608	0.234
LSTM	0.6754	0.1004	0.0613	0.2766
VepNet	**0.7307**	**0.1186**	**0.0741**	**0.2979**

Hyper-parameter tuning and Optimization

VepNet is implemented using Tensorflow [2]. The dimensionality of LSTM hidden state is 128, and the dimensionality of the attentional hidden state is 256. The model was trained via the Adam optimizer (Kingma and Ba 2014), with an initial learning rate of $1e-3$ and batch size of 64. Random search is used for hyper-parameter tuning (Bergstra and Bengio 2012).

Prior signals of the eruptions

In this part, we attempt to extract the learning knowledge from VepNet to explain the prior signals of the eruptions. VepNet utilizes two hours (120 minutes) of 4 type of data to make the prediction. According to domain knowledge, some abnormal signals last for approximately 10 minutes which triggers the eruptions. The whole idea of attention layer is to figure out which signals are the triggers. 120-minute data can be split into 12 intervals with 10 minutes each. Some intervals have higher attention scores than others. The set of data which shares high attention scores at the same interval is likely to share some common signals. Such set of data is visualized in one figure to investigate the data as we believe

[2] https://www.tensorflow.org/

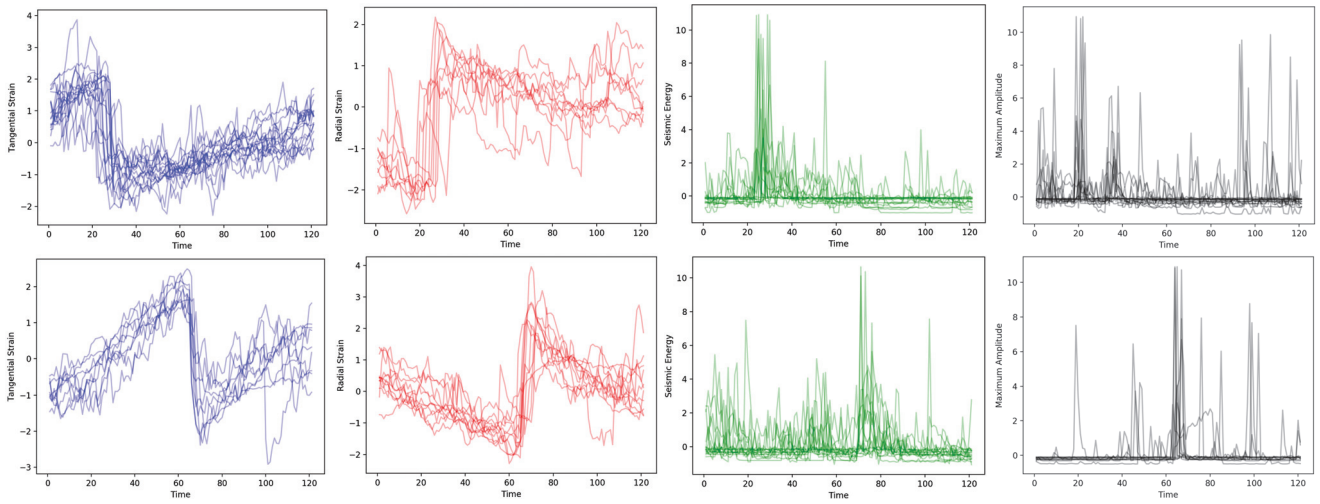

Figure 4: The visualizations of 4 types of data having the high attention scores around minute 30 (top) and minute 70 (bottom).

that the shared common signals could be the triggers of the eruption. We later consult with volcano experts to verify the information we have learned from this visualization to confirm the correctness of the assumption. Due to the page limit, we only show the visualizations of two intervals: high attention scores around minute 30 and minute 70 of the data. The visualizations are shown in Figure 4. It is interesting to notice that the tangential strain data (blue lines) has a sharp drop at the location where the attention scores are high. Similarly, radial strain data (red lines) has a sharp increase, seismic energy data (green lines) and maximum amplitude (black lines) data have the peaks. Volcano experts confirmed that these signals are generally well-known for the prior signals of the eruptions at Sakurajima volcano. However, it is hard for experts to know the thresholds of these patterns, for example how much the signal drops, to make the prediction. VepNet can detect these prior signals automatically and is potential for further investigation of the pattern thresholds.

Proposed 3-Level Warning System (3LWS)

When an eruption occurs, a huge amount of dust and ash will be emitted from the crater, which extremely affects people's health and daily life (Blong 2013). Therefore, there is a need to have an eruption warning system in real-time. Based on the promising results from VepNet, we developed a system at Sakurajima volcano which issues the eruption warning hourly. This system is for the convenience of people's lives, not for evacuation's purpose because we predict all eruptions. Therefore, it is normal to have many warnings. The system for evacuation plan should consider predicting large-scale eruptions only.

In this system, we categorize the warning into three levels: Low Risk, Medium Risk, and High Risk. Low Risk means less likely that there will be an eruption, High Risk is likely to have eruption, and Medium Risk is the middle level. Using the output from VepNet, we define two optimal cut-off points for High Risk and Low Risk based on the cost of False Negative and False Positive from domain knowledge. Medium Risk will take the threshold between these two cut-off points. The cut-off point for Low Risk is the threshold at which the number of False Negative cases should be small. This is important because people will not prepare for the eruption at all. Hence, the cost of False Negative should be high. Taking domain knowledge into account, the cost ratio of False Negative and False Positive is 20:1. In contrast, the cut-off point for High Risk is the threshold at which the number of False Positive cases should be small. As False Negative is always severe, the cost ratio, in this case, is equally 1:1. The cut-off point will be the threshold where the cost is minimum in each case. The visualization of cost for two cut-offs is shown in Figure 5. From the cost curve, the optimal threshold for Low Risk is 0.1942, and this figure for High Risk is 0.8236. Medium Risk will take the threshold between 0.1942 and 0.8236. Because the eruption warning will be predicted in three levels hourly, we call this system 3-Level Warning System (3LWS).

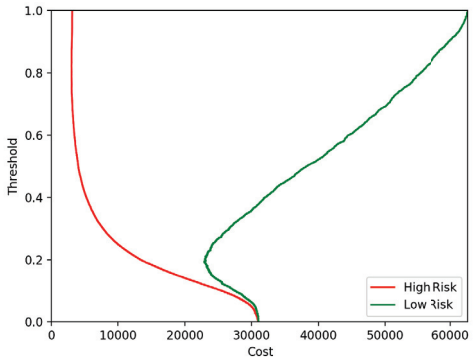

Figure 5: The visualization of cost curve with respected to threshold of Low Risk cut-off and High Risk cut-off.

The prediction result of 3LWS is shown in Table 3. We

Table 3: The performance of 3LWS. Abbreviation: Eruption Rate (ER).

Year	**2013**			**2014**			**2015**			**2016**		
Risk	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Total	4,713	3,549	158	5,406	3,191	87	5,899	2,463	249	7,960	648	51
Eruption	102	540	100	62	287	60	116	387	139	24	18	5
ER (%)	2.16	15.22	63.29	1.15	8.99	68.97	1.97	15.71	55.82	0.3	2.78	9.8

evaluated the performance in four years from 2013 to 2016. The eruption rate is the number of eruptions over all the predicted cases for a given level. 3LWS achieved a low eruption rate in Low-Risk level in four years. The highest eruption rate in Low-Risk level is 2.16% in 2013. This means that when the system issues a Low Risk, 97.84% there is no eruption. The Medium Risk level has up 15.71% eruption which is not high, but still, people need to be careful. In the High-Risk level, the model made good warning with the eruption up to 68.97% in 2014. In 2016, because the class imbalanced problem is extreme, 3LWS had some trouble in prediction. Nevertheless, we can observe that the system issued a large number of Low-Risk levels and a small number of High-Risk levels compared to previous years. This shows that 3LWS was aware of a year of not many eruptions. 3LWS can issue warnings with high accuracy and reliability.

Conclusion

Short-term prediction of volcanic eruptions is a challenging and important task. It is hard to even for volcano experts to make the prediction. In this paper, we researched the short-term prediction of volcanic eruptions using machine learning on two perspectives: traditional and deep learning approaches. We then proposed a modern architecture named VepNet to predict the eruptions of Sakurajima volcano hourly. By employing a stacked LSTM, VepNet can learn the high-level nonlinear and time-dependent features from the sensor data. On top of LSTM, we stack an attention layer which plays a role as a selector to automatically weight the contribution of each time step. This layer helps to increase the accuracy of the prediction and at the same time provide the interpretation to the eruptions. Experimental results on the real dataset from Sakurajima volcano, which is the largest dataset about volcanic sensor monitor in Japan, showed that VepNet outperformed the other models. The analysis showed that the attention mechanism provided meaningful interpretation by focusing on some interesting patterns of the eruptions. From the promising result of VepNet, we proposed a 3-Level Warning System to issue the eruption warning hourly. The system can issue the warning with high accuracy and reliability.

Acknowledgments

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