Classification of Volcanic Ash Particles with a Convolutional Neural Network on RGB Microphotographs: Towards Real-Time Monitoring of an Ongoing Eruption

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Abstract

Real-time monitoring is vital for timely hazard evaluation during ongoing volcanic eruptions. The component fractions of volcanic ash particles have been used as a proxy for eruption style. However, continuous real-time monitoring of the components in airfall ash has not yet been realized, because manual classification is time-consuming and the criteria for the classification are subjective. In this study, we used a convolutional neural network (CNN) method to classify volcanic ash particles from the 2014–2016 activity at Aso volcano, Japan, using microphotographs taken as red–green–blue (RGB) images that capture the ash surface microstructures. We trained the CNN algorithm using 512 images of five categories of ash particles which were based on color, vesicularity, glassiness, alteration and crystal fragments from two ash samples. Component analysis was then undertaken on six ash samples using the trained CNN. The component fractions obtained by the trained CNN are consistent with those from a manual classification based on observations with a stereoscopic microscope. The trained CNN successfully classified 518 particles in the microphotographs within 3 min. Thus, we conclude that component analysis by the CNN method using RGB microphotographs could be applied to quasi-real-time monitoring of an ongoing eruption.

Key words: Volcanic ash particle, Machine learning, Convolutional neural network, RGB microphotograph, Volcano monitoring

1. Introduction

Real-time monitoring is vital for hazard assessment during an ongoing volcanic eruption. Component analysis of volcanic ash particles should be included in real-time monitoring because the component fraction provides direct evidence of eruption processes determining the possible hazard [1)-4)] and does not require complex methods or preparation to characterize the erupted products. However, component analysis by manual classification under a stereoscopic microscope is difficult to incorporate into real-time monitoring, because it is time-consuming and the classification criteria are subjective. For manual classification, it takes approximately half a day to classify the ash particles in a representative sample. As a result, the time required for analysis can lag behind the changes in eruptive activity. The criteria for manual classification can also vary with time, particularly when multiple operators are involved in the classification during long-term activity. Therefore, further research is needed to develop methods for the component analysis of volcanic ash particles so that it can be used as a continuous real-time monitoring tool.

A convolutional neural network (CNN) is a deep-learning algorithm for objective image recognition[5)-7)], which may be applicable to component analysis of volcanic ash particles[8)]. A CNN contains multiple layers that convolve the pixel intensities, sends the convoluted signals to the next layer, and then finally outputs the probabilities that the object being evaluated falls into each classification category. A CNN for

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image recognition is trained using labeled images and by minimizing the classification error rate. Shoji *et al.* (2018)[8] used a CNN to classify volcanic ash particles based on their shape, which is related to eruption style and fragmentation process[9)-14)], and demonstrated that a CNN can classify types of juvenile ash particles in typical basaltic eruptions, based on particle shapes observed in 2D monochromatic microphotographs taken under transparent light. However, surface microstructures such as glass texture and ash particle color were not included in their classification.

Surface microstructure is a fundamental descriptive parameter of a volcanic ash particle[15)-17)] and provides insights into the eruption style[1), 18)-22)]. Ash particles that originate from newly ascending magma are expected to have a glassy appearance due to rapid quenching during magma fragmentation, whereas particles that originate from stagnant magma or recycled material will not be glassy due to the micro- and nano-scale crystallization of groundmass glass in the shallow conduit[1), 23)]. In addition, the color of ash samples changes with eruption style[22)] and the involvement of hydrothermally altered material[20)], and may be an indicator of a phreatic eruption[2), 18)].

In this study, we applied the CNN method to the classification of volcanic ash from the 2014–2016 activity at Aso volcano, Japan, using colored red–green–blue microphotographs. We show that this method provides a robust classification of volcanic ash particles that could be utilized in real-time monitoring of an ongoing eruption.

2. Sample

This study is based on six ash samples from the 2014–2016 activity of Nakadake first crater, Aso volcano, Japan (**Table 1**). Two ash samples collected on 15 December 2014 and 15 December 2016 (Aso-03 and 05, respectively) were used to obtain images for training the CNN, because these samples contain typical particles to describe characteristics of volcanic ash from the activity at Aso volcano. All six samples were used for classification using the trained CNN and manual classification. All samples were collected within a few days of deposition. The ash samples were washed in distilled water in an ultrasonic cleaner for 30 s to remove very fine particles which disturb observation of the surface microstructure, and dried in an oven at 80°C for 24 h. The dried samples were sieved to obtain ash particles of 250–500 μm in size. This size range is abundant in all samples used in this study and is large enough to allow microstructures to be observed.

The ash particles in the samples were classified into the following five categories (**Fig. 1**): black, glassy, and vesicular (BGV); black, glassy, and dense (BGD); black and non-glassy (BN); altered particle (AL); and plagioclase (PL). This classification is based on the phases present, glass features, color, and presence of vesicles. BGV and BGD have glassy surfaces with and without vesicles, respectively. BGV and BGD are interpreted to be the juvenile material of the eruptions[18), 23)]. BN particles have a non-glassy surface, black to gray color, originated from old lava or recycled material[1), 23)], and are interpreted to be lithic particles. AL particles show evidence of alteration and a wide range of colors, including gray, white, red, and yellow[18), 23)]. PL are plagioclase crystals that may have a thin rim of groundmass. Mafic minerals were not considered because they are only present in small amounts (<5 vol.%).

Table 1 Samples.

	Sample collection		Number of particles classified	
	Date	Time	Manual	CNN
Aso-01	2014/11/26	18:20	103	107
Aso-02	2014/12/10	10:30	105	93
Aso-03	2014/12/15	14:35	164	100
Aso-04a	2014/12/26	15:40	90	72
Aso-04b	2014/12/26	16:00	112	69
Aso-05	2016/10/9	13:18	161	77

3. Methods

3.1 CNN training

This study used RAPID machine learning software developed by NEC Advanced Analytics. RAPID is software for deep-learning based on a CNN, which contains input, convolutional, normalized, max pooling, fully connected, softmax, and output layers (**Fig. 2**). An appropriate network is selected according to the dimensional size of input image. The network is automatically configured and the particle image is convolved. The number of network layers and kernel size are automatically determined, but the number of channels can be varied; the best classification accuracy for the current dataset was obtained when the number of channels was set to 16. The detailed algorithm for the determination of number of network layers can not be shown here, since the RAPID is commercial software. The CNN in the RAPID software is trained using labeled images and by minimizing the error classification rate. The error rate is defined as the ratio of the number of errors to the number of training data in an epoch of training. A decreasing error rate represents progress in the training. We set the number of training epochs to 60, but manually stopped the training when the error rate was sufficiently converged to avoid overfitting the dataset.

Microphotographs of ash particles which is composed of only one of the five basal categories (BGV, BGD, BN, AL,

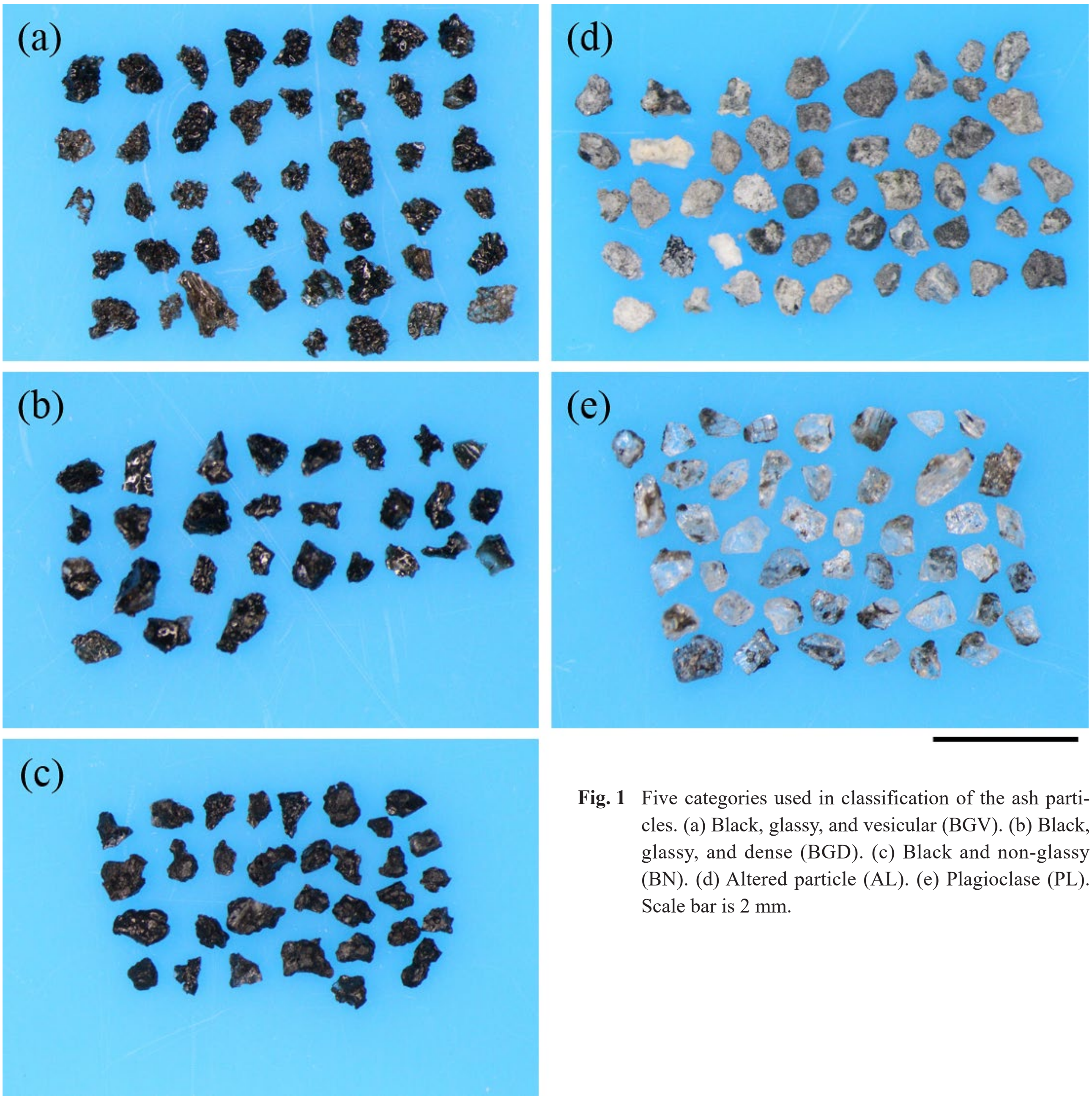

Fig. 1 Five categories used in classification of the ash particles. (a) Black, glassy, and vesicular (BGV). (b) Black, glassy, and dense (BGD). (c) Black and non-glassy (BN). (d) Altered particle (AL). (e) Plagioclase (PL). Scale bar is 2 mm.

and PL) were taken under a stereoscopic microscope to use in the CNN training and classification (**Fig. 1**). Representative particles of the five category of ash particle from two samples (Aso-03 and 05) were manually placed on a light blue colored plastic plate such that the particles did not overlap, and then microphotographs were taken with a digital camera (Canon EOS Kiss X71) attached to a stereoscopic microscope (Nikon SMZ800) under incident light. We carefully select the representative particle for the five categories by observing the all faces of the particles and determined that for representative particle when the all faces have characteristics of same category. The microphotographs were three-channel RGB images in JPEG format. The microphotographs were 1280 × 1028 pixels in size with a resolution of 5 μm/pixel, which is sufficient to observe the microstructure of the ash particles. Thirty to fifty particles were captured in each microphotograph. An image of each particle was extracted from the microphotographs by thresholding of pixel intensity and resized to 256 × 256 pixels in RAPID software.

The extracted particle images were used as labeled images for training of the CNN using RAPID software. A total of 120 extracted particle images were picked for the each category (BGV, BGD, BN, AL, and PL). As pre-processing for training, the number of images was increased by image processing, such that the brightness and saturation of the images were varied by ±20%–40% and the images were tilted by 90°, 180°, and 270°. As a result of the image processing, the 512 particle images yielded a total of 2560 particle images for training.

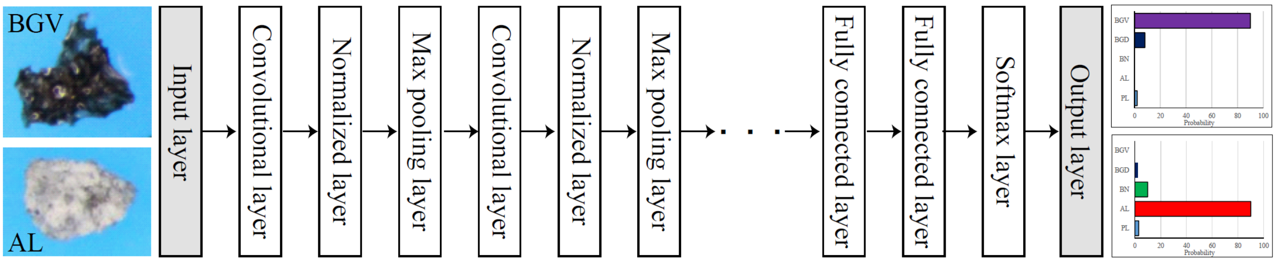

Fig. 2 Schematic structure of the RAPID software used for the deep convolutional neural network method.

3.2 Component analysis using the trained CNN

The RGB microphotographs of the six ash samples were subjected to component analysis using the trained CNN (**Table 1**). The ash particles were randomly taken from each sample and placed on a light blue plastic plate. We took three or four RGB microphotographs of each sample under the same conditions (aperture, white balance, iso, and shutter speed) as for the images used in the CNN training. The RGB microphotographs were analyzed with the trained CNN, which outputs the probability that the particle being evaluated falls into each category. The probabilities were evaluated for each particle, and the particles were classified into the category of highest probability. The component fractions of the five categories were then calculated for the six samples by counting the number of particles classified into each category. The classification was done for all particles taken in the RGB microphotographs. The number of classified particles ranged from 69 to 117 for the samples, resulting in a total of 518 classified particles (**Table 1**). The classification was finished within 3 min using a personal computer with 1.8 GB of RAM and a 2.30 GHz CPU.

3.3 Manual classification under stereoscopic microscope

To compare with the classification by CNN, we evaluated component fraction of the six ash samples by manual classification under stereoscopic microscope.

4. Results and Discussion

Fig. 3 shows the error rates of the training as a function of epoch. The error rates rapidly decreased within 10 epochs and mostly converged by 30 epochs. Therefore, we used the trained CNN built over 30 epochs, for which the error rate is ~1% for the current dataset.

We tested the trained CNN on five particle images for every each category which were not used for the training. In the categories of BGV, BN, and PL, a 100% accuracy was achieved, while in the categories of BGD and AL, accuracy rates of 60% and 75% were obtained, respectively. The BGD was misclassified as BGV and BN. The BGV is glassy particle with vesicles, while BN is non-glassy particle which almost lack vesicles. It is considered that BGD was misclassified into BGV and BN because BGD is glassy particle without vesicles having intermediate properties between BGV and BN. Additionally, AL was misclassified as PL. This may be attributed that AL often appearing white, and the high brightness observed in PL being seen as white color in the images.

The classification results obtained by the trained CNN are generally consistent with those of the manual classification (**Fig. 4**). The classification using the trained CNN tends to output a higher fraction of juvenile material (BGV and BGD) than the fraction by the manual classification method. This is because the manual classification, which is in 3D, rejects to identify ash particles as juvenile particles even in the case of only a small amount of AL or BN being evident in the particle. In the CNN classification, which is in 2D, the ash particles are only observed from a single direction and, even if there is AL or BN present in another plane, the particle is classified as juvenile. The texture of ash particle is generally heterogenous and sometimes contains parts classified into some categories even in a single particle. The classification results indicate the contribution of juvenile material increased from November to December 2014, and AL particles dominate the ash sample collected from the discrete eruption on 8 October 2016, which might reflect a change in eruption style. Compared to the other samples, Aso-05 used in the training shows a larger difference between the results from CNN and manual classification. This may be because the texture of AL which occupies the majority is similar with that of BN in Aso-05.

Component analysis of volcanic ash particles by the CNN method could be applied to quasi-real-time monitoring of ongoing eruptive activity. This method also successfully classified the volcanic ash particles in the samples that contained lithic and altered particles, by taking account of surface microstructures. This advance is useful for monitoring eruptive activity because these types of particles provide clues to eruption style[1), 2), 18), 20), 24)]. In addition, the trained CNN successfully classified 518 particles within 3 min, which is shorter than the typical timescale of changes in eruptive activity[2), 23), 25)]. The time scale of the CNN classification is a results of sum of the time scales. Approximately 12 hours for transportation of ash sample from the field to laboratory.

10 minutes washing. 20 minutes drying. 1 minute sieving. 15 minutes for taking photograph. Image transfer and processing are 3 minutes. Although the data processing time is too long for real-time monitoring, it is sufficient for quasi-real-time monitoring if the collection and preparation of ash samples can be done in the field. Moreover, the classification based on the CNN is objective and consistent over the duration of an eruption event, which is important when the eruptive activity is prolonged. Finally, we suggest that the combined observation of CNN classification with the automatic onsite imaging of ash particles in the field which reduces the time of transportation of ash sample[26] sufficiently contributes quasi-real-time monitoring of style of an ongoing eruptive activity.

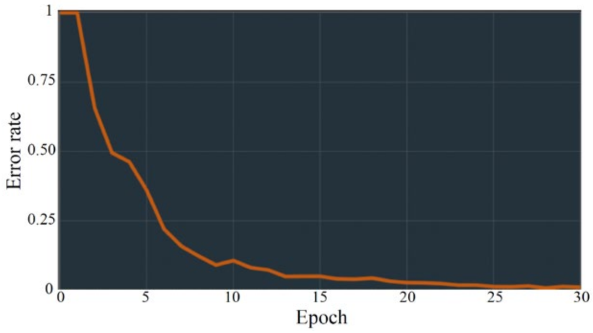

Fig. 3 Error rates of the classification as a function of the epoch number.

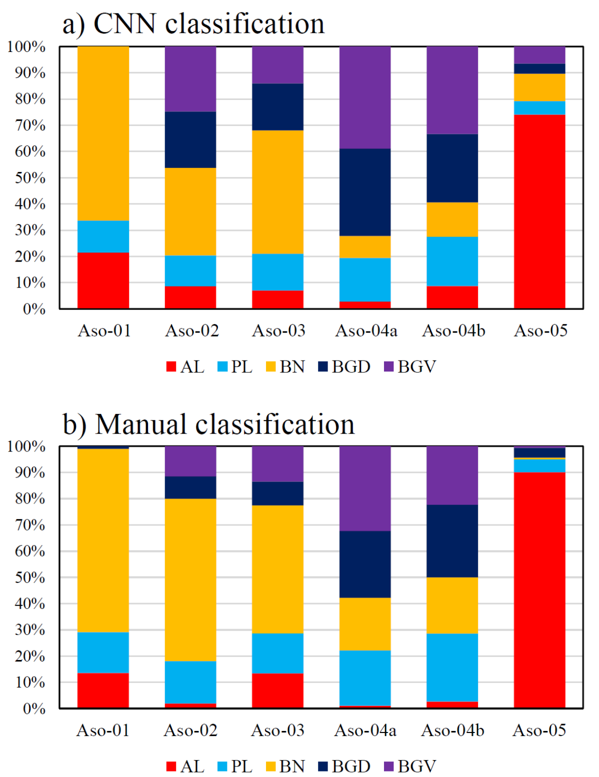

Fig. 4 Comparison of component analysis results from (a) the CNN and (b) manual classification methods.

5. Conclusions

We used the CNN method to undertake a component analysis of volcanic ash particles from the 2014–2016 activity at Aso volcano, Japan. The component analysis by the trained CNN is consistent with that by manual classification, and succeeded in classifying volcanic ash particles in samples containing lithic and altered particles. The trained CNN successfully classified 518 particles in the microphotographs within 3 min. Therefore, we conclude that component analysis by CNN on RGB microphotographs of ash particles can be used for quasi-real-time monitoring of ongoing eruptive activity.

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RGB 顕微鏡画像を用いた畳み込みニューラルネットワークによる火山灰粒子の分類
−進行する火山噴火のリアルタイムモニタリングに向けて−

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要　旨

噴火様式の連続リアルタイムモニタリングはハザード評価に不可欠である．火山灰粒子の構成物比は噴火様式のプロキシとして用いられてきた．しかし，火山灰構成物比のリアルタイムモニタリングはまだ実現されていない．本研究では，畳み込みニューラルネットワーク (CNN) と RGB 顕微鏡写真を用いて，2014 年から 2016 年にかけて噴出された阿蘇火山の火山灰粒子を分類した．我々は，2 つの火山灰試料の粒子を 5 つのカテゴリに分類し, 計 512 枚の画像を用いて CNN アルゴリズムに基づく学習を行った．次に, 学習させた CNN を用いて, 6 試料の構成物解析を行った．その結果, CNN による構成物比は, 実体顕微鏡観察に基づく分類結果と調和的であり，また顕微鏡写真中の 518 個の粒子を 3 分以内に分類することに成功した．以上から，RGB 顕微鏡写真と CNN を用いた構成物解析は，噴火の準リアルタイムモニタリングに適用可能であると結論できる．

キーワード：火山灰粒子，機械学習，畳み込みニューラルネットワーク，RGB 顕微鏡画像，火山観測