Classification of Track Types in Tanpopo Mission by Deep Learning Y. Miyamoto[1], H. Demura[1], K. Okudaira[1], H. Yano[2], A. Yamagishi[3], [1]ARC-Space, University of Aizu (Ikki-machi, Aizu-wakamatsu City, Fukushima Pref. 965-8580, JAPAN; okudaira@u-aizu.ac.jp), [2]Institute of Space and Astronautical Science, Japan Aerospace Exploration Agency, [3]Tokyo University of Pharmacy and Life Sciences (Professor Emeritus).

Introduction: "Tanpopo" is a Japanese astrobiological space experiment on the International Space Station [1]. In its capture experiment, micrometeoroids containing organics or terrestrial microbes entering/leaving the Earth, and space debris are expected to be collected by silica aerogel panels (ultralow-density amorphous glass with box-framing structures [2].

Cavities in the aerogel formed by the particles are called "tracks", and their shapes are roughly correlate with the particle size, entering speed, and physical properties of the captured particles [3]. Visibility of tracks in this Tanpopo mission differs from that of STARDUST mission because transparency of the aerogel connected with bulk density (e.g. [1], [3]). The density of aerogel for Tanpopo is 0.01 g/cc.

The tracks are processed CLOXS (Captured particles Locating, Observation and eXtraction System) [4] developed in the Tanpopo mission for initial analysis, and its generated data are archived in the database. Most of the analysis procedures do not include manual handling.

Objective of this study: In this research, we use deep learning to verify the validity of the qualitative four-type classification of tracks performed by humans.
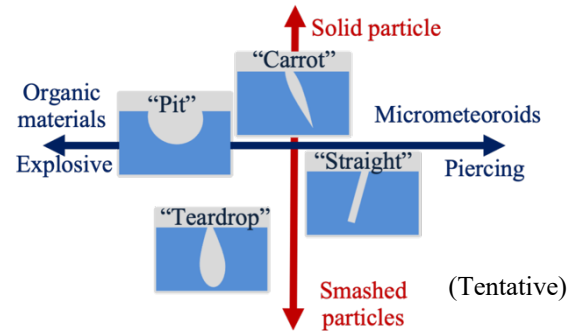
Dataset: Tanpopo mission team has brought a small-scale set of labeled tracks with four types; Carrot, Pit, Straight, and Teardrop. These images are produced by CLOXS. Original dataset is shown in Table 1. This dataset is down-sampled around 80~90 images because the number of each type is unbalanced. The training and test sets are split from the dataset in the ratio, 2:1.
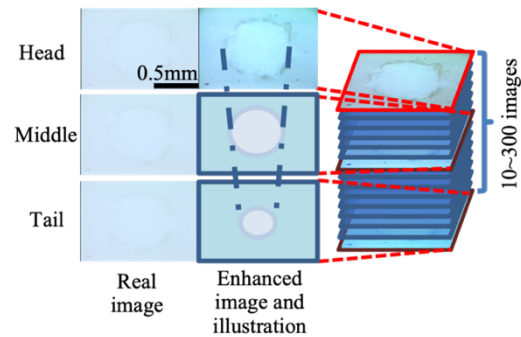

Fig. 1: Track shapes with 2 axes of physical properties

Fig. 2: Three images per track; Head, Middle, and Tail

Table 1: All track types and their number

Track Type	Number of Tracks
Carrot	172
Pit	82
Straight	75
Teardrop	202
	Total: 531

Track type has a relation with the physical properties of particles [3] [5]. Figure 1 shows track shapes in cross-section with two axes of physical properties of particles; explosive ~ piercing, solid ~ smashed.

We standardize the length of tracks by adopting three images a track; head, middle, and tail in Figure 2, because the least configuration of sequential images per track is a set of three images. Preprocessing is CLAHE (Contrast Limited Adaptive Histogram Equalization), Gamma correction, Median filter, Center crop into 700 x 700 from 704 x 480 and resize 224 x 224. The values for normalization are mean [0.325, 0.419, 0.444] and std [0.220, 0.284, 0.301].

Methods: We used two machine learning models: ResNet50 (Residual Network) [6] and MVCNN (Multi-View Convolutional Neural Network) [7].

On ResNet50, two models train with images one by one. One is the original ResNet50 model, and the other is ResNet50 + MLP. This MLP (Multi Layer Perceptron) is not same with MVCNN original model but this is generated based on the model. In addition, these models train with two patterns dataset; only use one image and three images. In the case of using one image, that image is the head. Three images are the same with MVCNN.

MVCNN is for a 3D graphics model, but our model uses only three images as one feature (Figure 3). Also, in this original model, the features replace with the maximum value same position in other features. In
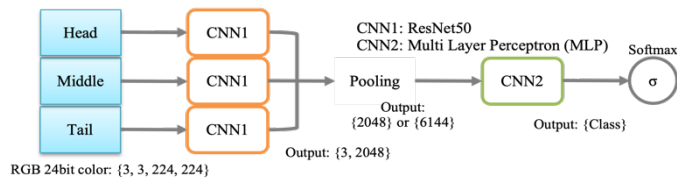
Fig. 3: MVCNN architecture; 2048 output is replace values of features, and 6144 is concatenated.

addition, we try the model to concatenate three image features. This way is an architecture based on the ViT (Vision Transformer) embedding [10]. The formula is

$$xi' = (n - i) / n * xi$$

The n is the number of used images, and

$$X = \{xi \mid i = 0, 1, 2, \ldots, n\text{-}1\}$$

is concatenated features.

Table 2 shows layers of models. These linear layers have GELU (Gaussian Error Linear Units) [8], but between softmax and linear layer do not have it. Also, ImageNet [9] previously train ResNet50.

Table 2: MLP layers on each models

	ResNet50 + MLP, MVCNN original		MVCNN-concatenate	
ResNet50	Input: 3, 224, 224		Output: 1, 1, 2048	
Layer	Input	Output	Input	Output
Linear1	2048	1024	6144	3072
Linear2	1024	512	3072	1024
Linear3	512	512	1024	512
Linear4	512	4	512	512
Linear5			512	4
Softmax	4	4	4	4

Results: Table 3 shows the results. ResNet50 models use individual images, while MVCNN model uses three images (as one unit) only.

Table 3: Experiments results

Models	Acc. 3 imgs	Acc. 1 img
ResNet50	57.778	55.238
ResNet50 Pre.	78.730	77.143
ResNet50 + MLP	59.365	59.048
ResNet50 + MLP Pre.	78.413	78.095
MVCNN concatenate	60.951	
MVCNN replace	82.857	

All pretrained ResNet50 models show relatively good accuracy. ResNet50 and added MLP model were not found significant differences when using three images. MVCNN with replacing maximum value shows best score.

Discussion and Summary: The accuracy of this classification meets required level in manual one. In addition, since the Tanpopo mission series is an ongoing project, the accuracy can be improved as more data becomes available. These track types are the original models for the other intermediate shapes and are based on the criteria shown in Figure 1. It is conceivable that the number of axes to be used as criteria among four types may increase from them.

We are extending this research to provide the recursive system with data mining. The system goes beyond simple track classification by deep learning and can replace the visual inspection of skilled users.

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