Authors' responds to Anonymous Referee 2:

We would like to thank the reviewer for the thorough review of our manuscript and insightful feedback. These comments have significantly improved the quality of our work. In the following sections, we present the reviewer's comments (in black), our responses (in red), and the changes made in the revised manuscript (in blue). Please note that all line numbers in our responses correspond to those in the revised manuscript.

Comments

1. I would recommend explaining why you have explicitly chosen these 19 categories. For example, why the difference between columns and aged_columns is important and relevant, or why you don't have an extra class for sectorial plates. Explain how easy it is to include different particle shapes such as spherical rosettes?

   The classification scheme in this study follows Zhang et al. (2024), who designed categories of ice crystals based on the basic habits and two microphysical processes (aggregate and aged). The main reason of choosing 19 categories is that the scheme is designed based on the NASCENT dataset in which 19 categories are identified. Following your comment, we add explanations about the reason we have 19 categories in the Data Section

   L87-L95

   …The scheme contains 7 basic habits identified by Pasquier et al. (2022b) from the ice crystal images collected and identified in mixed-phase clouds of Ny-Alesund during the NASCENT campaign (Pasquier et al., 2022a). When combined with two microphysical processes: aging and aggregation, these basic habits develop into 12 complex shape categories, after excluding combinations that were not feasible. Among the 7 basic habits, the "Plate" and "Column" formed due to deposition growth under different temperature and supersaturation conditions. "Lollipop" (Keppas et al., 2017) forms by a droplet freezing on a columnar ice crystal, or the columnar part is the result of depositional growth on a frozen droplet. "CPC (columns on capped-columns)" originated from cycling through the columnar and plate temperature growth regimes, during their vertical transport by in-cloud circulation (Pasquier et al., 2023). Ice crystals that are too small for shape determination are categorized as 'Small', while large crystals with indistinguishable shapes are categorized as 'Irregular' '. As for the two microphysical processes…

   In terms of the detailed criteria for manually classifying ice crystal, it was comprehensively discussed in the appendix of Zhang et al. (2024).

   The shape of ice crystals plays a crucial role in atmospheric processes, as mentioned in the introduction. Different shapes exhibit varying radiation properties, which ultimately influence Earth's radiative forcing. For example, Wendisch et al. (2007) had shown the upwelling irradiances reflected by cirrus cloud is significant shape dependence. Additionally, the shape of ice crystals affects precipitation formation and determines the type of precipitation that reaches the ground. For example, heavily rimed ice crystals such as aged column may leads to hail eventually.

The scheme does not include other ice crystal shapes, such as sectorial plates, as these were not observed in the dataset collected during the NASCENT campaign. Their absence can be attributed to the temperature and supersaturation condition were not in favor of the formation of these shapes.

The classification scheme is flexible and can include other shapes like spherical rosettes. Researchers can adjust the categories after they determined the basic habits, and the microphysical processes based on the dataset they own. Besides, the CSSL algorithm is flexible and can easily adapts to new dataset that are not used in our original dataset. The architecture of CSSL algorithm separate the feature learning (unsupervised pre-training) and specific downstream task (classification), which make it flexible enough to handle new dataset as it can be fine-tuned on only a few labeled images, as shown in Section 5.2. We add some discussion about the flexibility of CSSL in the Section 6.

L446-L450
…It shows promising potential of adapting to new datasets that are not used in training. The architecture of CSSL algorithm separates the feature learning process and the specific downstream task, which makes the model flexible to classifying new datasets through only fine-tuning on relatively few labeled examples. As the model has learnt the features of ice crystal in the upstream network, it can also adapt to data collected using different imaging devices…

2. Question about Figure 1: Are the sample images arranged randomly, or is there a reason for the arrangement? If it is random, I think it would be clearer to have similar groups together. I also wonder if the Column_and_aggregated image in the first row, second place, isn't more of a Lollypop_aged_aggregate, but that group doesn't exist.

   No, it was not arranged randomly. It was arranged according to the distribution of ice crystal categories in NASCENT19 dataset. In the left panel, the order of the Y-axis labels is based on the number of images in each category in the NASCENT19 dataset, from largest to smallest. To make it easier for readers to match the category names in the left panel with the corresponding images in the right panel, we have listed the images one by one in the order of the Y-axis labels from top to bottom. The correspondence of left panel and the right panel is as follows:

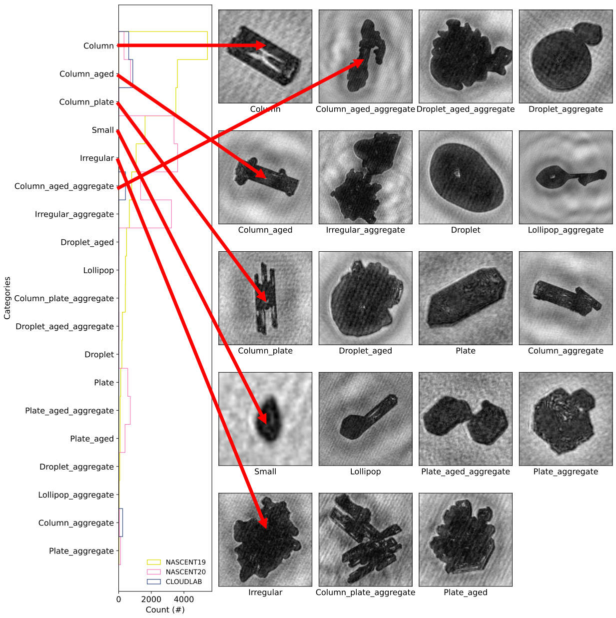

Figure 1: The correspondence of the left panel and the right panel

A Lollipop ice crystal forms by a droplet freezing on a columnar ice crystal or a frozen droplet forming a columnar part through deposition growth. The 'column_aged_aggregate' in the first row is a two heavily rimed 'column' aggregate together, which does not exhibit patterns of a freezing droplet.

3. In line 90 you write: 'Ageing' means that the ice crystals undergo processes such as riming, melting or sublimation. I would recommend that you consider whether it is possible to distinguish between riming, melting or sublimation, and whether this consideration is worthwhile or not?

   Thanks for commenting about the definition of ageing. We recognize the difficulty to distinguish between riming, melting and sublimation just from images within our dataset. Therefore, we used 'aged'/'ageing' as a category to include riming, melting or sublimation so that we can avoid misclassification of the CSSL algorithm. It also provides researchers the flexibility to further divide 'aged' category to riming, melting or sublimation when considering extra information such as the air temperature.

   In terms of the detailed criteria for manually classifying ice crystal, it was comprehensively discussed in the appendix of Zhang et al. (2024).

4. In 3.1 you say that it is important for unsupervised algorithms to add additional samples to the dataset by converting images into different versions. I would recommend discussing up to what number of particles this first step is even necessary. Because if you have a lot of (e.g. more than a million) unlabelled particles. Isn't this more necessary for the second step, so that you have more labelled particles?

Thanks for your comment about data augmentation. In contrastive unsupervised learning, data augmentation is principally essential, as we mentioned in Section 3.1. The algorithm requires different versions of the same image to learn, as it works by comparing these variations and measuring their similarities to compute the loss function. This need for multiple image versions exists regardless of the training set size, because the core principle of contrastive learning relies on the algorithm's ability to recognize that different augmented views of the same image should be considered similar, while views of different images should be treated as dissimilar.

In fact, during the supervised fine-tuning, the data augmentations also exist for increasing the number of samples. We now add this description in the manuscript to make it clearer.

L163-L167
During fine-tuning, data augmentation aims at expanding the size of our training dataset, which prevents overfitting (Shorten and Khoshgoftaar, 2019). The data augmentations during supervised fine-tuning include random cropping and random flipping. The input images in the downstream network are firstly resized to 256 × 256, and then they are cropped with area ranging from 60% to 100% randomly. Finally, they are randomly flipped before imputing into the CNN.

5. Typos.
   Fixed, thanks

References

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