Determining the shape and morphology of ice particles is important because it provides a fingerprint of the cloud processes taking place. Chu et al. 2024 present a new ice particle shape recognition algorithm (contrastive semi-supervised learning algorithm - CSSL). CSSL is based on two steps, unsupervised training (upwards) and supervised fine-tuning (downwards). This method is new because the older methods are either fully supervised or based on feature analysis. In either case, a lot of manual hand labeling effort was required for training and evaluation. The aim of the study is to show that with the new CSSL algorithm it is possible to achieve similarly accurate shape discrimination with less manually labelled data. For this purpose, CSSL was trained and tested in three recent studies using images from a holographic imaging device.

Chu et al. 2024 highlight two points:

1. They show that their new algorithm requires only a small fraction of the particles to be labelled to achieve similar accuracy, saving many hours of labelling work.

2. They point out that the performance of classification models depends on the distribution of ice crystal categories and that this applies to all types of algorithms.

The article by Chu et al 2024 is new and shows that it is possible to distinguish particle shapes with less time spent labelling particles. The question of how many shape categories actually make sense remains open, but should be discussed in the future. The data set also seems a bit small and should definitely be expanded to include more different cases. Other shape categories could emerge, resulting in a different distribution of particle shapes.
The study by Chu et al 2024 is relevant to the community. It would be particularly helpful and useful if the algorithm could be made available to everyone on Github. After some minor improvements, this study can be published.

I have a few 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?

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.

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?

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?

Typos and Image improvement:

Line 90: "aggregate".in → "aggregate" in

Line 92: "For example, in the case of riming, the image of aged crystals usually show a softly textured edges, which represents the supercooled droplets freezing on them."
Change either to: the image… shows … edge
or: the images …show … softly textured edges

Line 116: fatures → features

Line 134: sections→ sub-sections

Line 251: Fullstop missing

For Figures 6, 7 and 11: Increase the distance between number and percentage. In Sum Actual/Sum Predicted, the number and percentage are not easy to read. The contrast between black and dark blue is not so good, maybe change it to white on dark blue.

I really like this figure 8, it shows so well how your algorithm works.