Referee Report for :

Exploring the effect of training set size and number of categories on ice crystal classification through a contrastive semi-supervised learning algorithm (egusphere-2024-3160)

The article presents a novel methodology aimed at enhancing deep learning techniques for recognizing ice crystal images. Analyzing the morphology of ice particles is crucial for understanding cloud ice formation, estimating their lifetime, and assessing their potential for precipitation. While convolutional neural networks (CNNs) have been successfully trained for this purpose, their effectiveness has been hindered by labor-intensive manual labeling, limited generalization capabilities, and strong dependence on the original training datasets, raising concerns about their objectivity.

To address these challenges, the new methodology employs a contrastive semi-supervised learning (CSSL) algorithm, which integrates both supervised and unsupervised learning approaches. This technique aims to reduce the need for extensive manual labeling while improving the objectivity and generalization of the trained models. CSSL models are tested against a fully supervised CNN trained on the same datasets of varying sizes in a thorough and well-structered set of experiments, however limited by the amount of available data.

The results indicate that while the CSSL approach is promising, its advantages over purely supervised CNN models are not immediately clear. Specifically, once the training set exceeds 2048 samples (a relatively small number) the performance of the fully supervised CNN matches that of the CSSL models. Additionally, the study acknowledges that classification performance still depends on the category distribution within the training dataset, classification of less-represented classes being less accurate. However, one CSSL model generalizes better than the fully supervised CNN. Therefore, the expectation is that with larger pre-training datasets, the CSSL approach will further enhance generalization and reduce manual labeling efforts even more, making it a more efficient and scalable solution for ice crystal classification.

Associated data sets, codes, and models are provided by the authors, ensuring reproductibility and adaptation for other data sets.

The quality of the article is good and the clarity has been improved to be more accessible to newcomers in deep learning. The methodology is valuable for researchers using in-situ cloud and precipitation particle imagers, making this study a useful contribution to the field. Given its strengths in methodology, accessibility, and reproducibility, I support publishing the article as is.