Project Proposal

Snowflake Morphology Classification Using Deep Learning

Ishtiaq Chowdhury, Ali Al Anbari

Dr. Ping Xu

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We propose a deep learning system for the classification of snowflake morphologies restricted to five pragmatic classes (dendrites, plates, columns, aggregates, graupel) based on camera images. This is an interesting problem scientifically and operationally, since the physical conditions (temperature, humidity, riming) the snowflake grew in can be determined by its shape and these conditions are needed for precipitation/weather/climate models. We will place this in context with a review of previous literature regarding automated classification of MASC (Multi-Angle Snowflake Camera) images and various characterization of snow particles (e.g., Hicks et al. 2019; Key et al. 2021) in addition to the reference description of the MASCDB data set which includes 0.85M triplets with rich descriptors and a standardization of access to the data for reproducible research. Our data will come from MASCDB from Zenodo, where we will keep only the class label contained in the metadata to the five intended types above, and split into train/val/test sets, while mitigating the class imbalance by sampling and augmentation. Methodologically, we will leverage EfficientNet-B2 as the backbone and will replace the classification head with a 5-class softmax. We have chosen EfficientNet-B2 for its strong accuracy-compute trade-off afforded by compound scaling, which is optimal for medium data sets as well in our constrained resource deployment situation. We will follow a 2 stage schedule: (1) training the new head while the backbone is frozen, (2) unfreezing all layers and fine-tuning end-to-end with small learning rates (AdamW), batch-normalization rates turned on, and label-preserving augmentation (random crop/flip and small rotations and mild jitter in color/contrast as appropriate for gray-scale or nearly-gray bodies). In order to keep the model light and cheap we will limit input resolution (possibly to 256–260 px). We will also use mixed precision and we will consider early stopping. We will track training/validation accuracy and loss per epoch, as well as the final accuracy of the test set, and qualitative error analysis (successes/failures) with a confusion matrix to show systematic confusions (messing up plates vs aggregates). We expect our EfficientNet-B2 fine-tuning will outperform scratch baselines, and achieve solid accuracy for the five classes in the subset, while having low inference costs.