

# The ICELEARNING project - Artificial Intelligence techniques for ice core analyses

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The idea of this project came up when I visited a marine lab at Bergen University and I saw an instrument that produces photos of visible particles dispersed in liquid samples. The instrument is called "FlowCam". I immediately thought that we could use this technique to analyze the insoluble particulate found inside ice core samples, which is routinely analyzed after melting, aka liquid. The resulting image dataset could be then crunched by machine learning techniques to try to classify the classes of insoluble particles that are found in ice records, which in general are: mineral dust (by far the most abundant), volcanic glass (also known as tephra), but also, depending on the coring site, terrestrial pollen, as well as marine particles which are at times found in coastal ice cores such as the Ross Ice Core in Antarctica. The crucial advantage is that the classification and thus the calculation of the impurity concentration (which is the main variable with a climate significance) would be automatic (with some accuracy), thus supporting and potentially surpassing manual microscopy, which is often the only viable solution to identify some of these particles.

The purpose of this document is to provide some information on the project concept and activities, currently stopped due to the covid-19 pandemic.

## 1. The project objectives

The aim of the project is the development of a technique for automatic insoluble particle classification in ice cores. It consists of two phases. During the first phase, which is analytical, ice core samples are melted and analyzed via liquid microscopy through the FlowCam. The result is a collection of particle images. The second phase is the development of classification models needed to perform particle identification in a supervised learning framework.

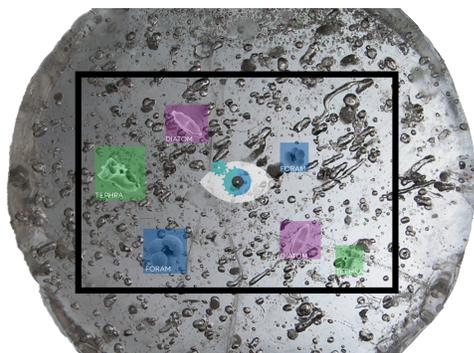


Fig. 1. Concept of the ICELEARNING project.

## 2. The project methods

**A. Liquid image microscopy.** The FlowCam instrument model we will use is a bench top VS-I-B model with monochrome

camera and Auto Imaging function. It can, theoretically analyze particles from 3  $\mu\text{m}$  to 2 mm using 2X, 4X, 10X or 20X magnification. Different flow cells will be tested, including field of view flow cells (FOV) that enable analysis of low concentration samples. The measurements are non destructive, meaning the water stream from the melted ice sample remains untouched and can be safely refrozen for other analyses.

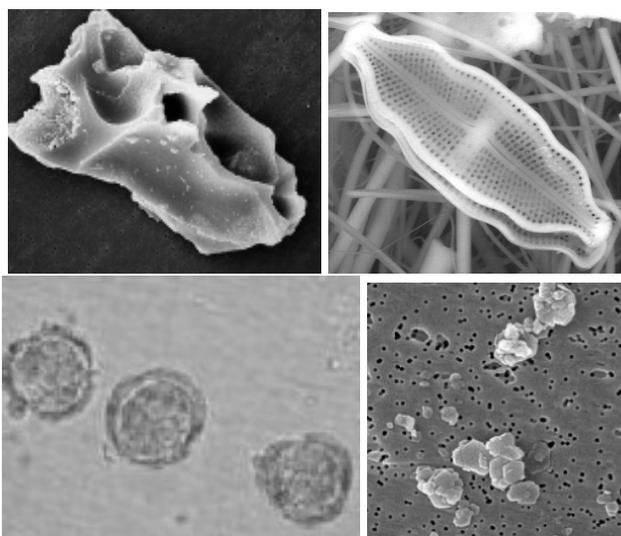


Fig. 2. Top-Left: a tephra from the GISP2 ice core. Top-Right: a *pinnularia borealis* diatom found in ice from the Quelccaya Summit Dome Glacier (Credit: Bruce Brinson). Bottom-Left: Artemisia pollen found in a Russian Altai mountain ice core (Credit: Jun Uetake). Bottom-right: Kaolinite dust grains in the Dome C ice core (Credit: Lorenc Cremonesi). Note that these images have not been acquired using FlowCam.

**B. Training datasets.** In every supervised learning exercise, training datasets are the necessary requisite. Also in this case, producing the training datasets for each one of the particles is the major challenge. We will build particle image training datasets using "standard samples" whenever possible. These include dust certificate materials with known size distributions, tephra samples, marine particle samples, etc. By analyzing

### Info

Project duration: 15 Jan 2020 - 14 Jan 2022.

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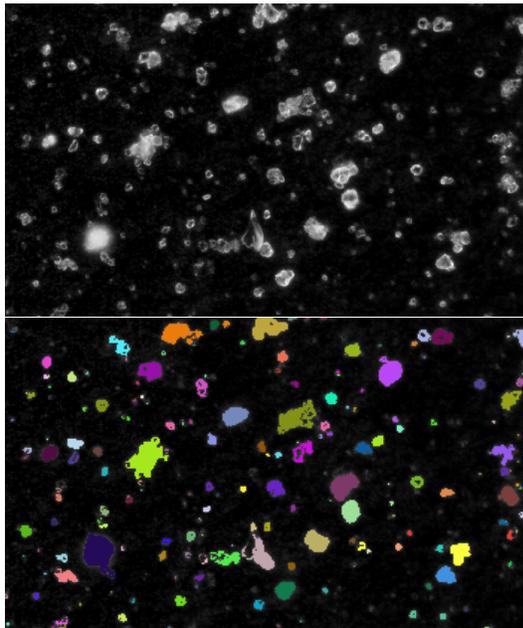


standards in the same conditions we will be able to obtain separate image datasets for each particle type.

**C. Classification and segmentation.** We choose a Supervised learning approach to separate particle classes. Neural networks and Convolutional Neural Networks (LeCun et al., 1999) will be developed. Various recently suggested architectures like U-Nets (Ronneberger et al., 2015) and other techniques such as Transfer learning will be explored.

Since mass concentrations are often the variable of climate significance (e.g. dust ice concentration is an important proxy for climate aridity), the mass has to be calculated. This problem invokes the calculation of the projected 2D area and from there, a transfer function is needed to convert area to volume and to mass. The calculation of the projected area is a segmentation problem. An example of ice core dust segmentation is shown in Fig. 3.

The results from the Neural Networks and the segmentation exercise will yield an "area" (actually a 2D-projection onto the camera plane). We will convert Area to Volume and from here to mass (if required) via a standard density value.



**Fig. 3.** Top: ice core dust deposited onto a filter. Bottom: the same image with dust segmentation. A mass distribution can be obtained from this exercise if the area  $A$  is converted to a volume  $V$  and to mass through a density value. This segmentation is just achieved by the Otsu's method. This simple implementation already provides a qualitative result. Maffezzoli et al. (unpublished).

**D. Feature engineering.** Instead of using the image raw pixels, it is often a smart choice to consider feature descriptors such as the histogram of oriented gradients (HOG) to investigate whether the classification tasks are facilitated by image pre-processing. We will explore several pre-training image descriptors during the course of the project.

### 3. Future implementation and project potentials

An analytical technique based on continuous liquid microscopy (CLM) coupled to an AI recognition technique (the latter can

be run offline) would be particularly beneficial and would naturally adapt to continuous flow analysis (CFA) setups (video link) through which ice core laboratories routinely process and analyze ice cores. These systems consist of a melt head which melts ice core sections, followed by an array of instruments for liquid and gas chemistry analyses. For insoluble particles, at present only the laser-based Abakus instrument for the continuous detection of ice core dust is implemented in CFA systems. Our suggested new technique would greatly increase the number of particles that could be detected continuously in CFA setups and (potentially) without the need of further manual microscopy performed on discrete samples. Another major advantage is that this methodology is non-destructive, therefore the water stream coming out can be safely reused for other destructive analyses.

Future Antarctic ice core projects, such as the Beyond Epica–Oldest Ice (BE-OI) Little Dome C ice core would feature ice greatly compressed at the bottom of the core length, thus non-destructive techniques to preserve as much as possible the sample requirements will be of paramount importance.

Another point worth stressing is that this technique will open up the possibility to investigate insoluble particles sourced from the ocean and scavenged onto ice sheets, providing information on past marine biology and ocean conditions via analyses of ice cores. If pollen and other terrestrial material is found, its detection can also provide clues on terrestrial biology and past vegetation extent existing within the ice core source region.

### Partners



### Funding



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### References

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