

# Identifying insolubles in IceCore data

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Figure adapted from: Bulat et. al. (2018). Unknown Widespread Iron- and Sulfur-Oxidizing Bacteria beneath the East Antarctic Ice Sheet. Paleontological Journal. 52. 1196-1203. 10.1134/S0031030118100076.



#### Identifying insolubles in IceCore data

#### June 17th, 2021















Area (ABD) Diameter (ESD) Area (Filled) **Edge Gradient** Aspect Ratio Elongation **Biovolume (Cylinder)** Biovolume (P. Spheroid)Feret Angle Min **Biovolume (Sphere) Fiber Curl** Circle Fit Circularity Circularity (Hu) Ratio Compactness **Convex Perimeter** Convexity Intensity Diameter (ABD) Length

Feret Angle Max **Fiber Straightness** Geodesic Aspect Geodesic Length Geodesic Thickness **Particles Per Chain** 

Perimeter Roughness Sigma Intensity Sphere Complement Sphere Count Sphere Unknown Sphere Volume Sum Intensity Symmetry Transparency Volume (ABD) Volume (ESD) Width

#### Preprocessing

- Scale pictures, such they can be used in a CNN
- Avoid overfitting by using same amount of data for each class in training



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## Meta data

Length

Sphere Volume Biovolume (Sphere) Intensity

'ameter

Inputpar

Roughness

Area (Filled)

Area (ABD)

Edge Gradient

Sum Intensity

Feret Angle Min

Biovolume (Cylinder)

Transparency

Geodesic Thickness Geodesic Lenath Perimeter Sigma Intensity Convexity

Width Circularity (Hu) Diameter (ABD)

Image analysis data of the pictures 

corvlus

camp

dust

grim

gsub

arob

0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 Mean(|SHAP value|)

LightGBM used for classification of the 6 types 

#### **General CNN structure**



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## Result: 6 model split

• Confusion matrix with custom loss function



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### Result: 3 model split

• Bayesian optimization (drop out rate, learning rate, size of layers)



## **Result: Subcatagorical split**

#### Combined model



#### Model performance

Model	Accuracy
6 split using, only Metadata	0.8347
6 split (Categorical crossentropy loss)	0.8791
6 split (Custom loss function)	0.8426
3 split	0.9806
3 split + subcategories	0.7628

### Prediction of the test data



## Picture size and inclusion of metadata

- Chose size 64x64
- With metadata



#### With metadata



#### Without metadata

Accuracy Score: 0.9525



## Unsupervised learning (UMAP): 6 model split



## Unsupervised learning (UMAP): 3 model split



## **Conclusion and perspective**

What we did:

- Data reduction/ standardization
- LightGBM
- Multiple structures of CNN's
- Optimization
- Loss function
- Visualization
- Scale of problem

Further ideas:

- Implementation of Loss function both models
- Implementation of optimization
- Handling of unbalanced datasets
- Better data structure so no limitations from hardware.
- Better anomaly detection across models

#### Identifying insolubles in IceCore data

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 Particle ID: GRIP\_3046\_0\_20\_1\_61191.png
 Particle ID: GRIP\_3046\_0\_20\_1\_55199.png

 Probability:
 Probability:

 Ash: 49.7%
 Ash: 49.76%

 Pollen: 0.69%
 Pollen: 0.58%

 Dust: 49.6%
 Dust: 49.67%



## 6 badly predicted test pictures

- 3 type classification using only metadata (see appendix)
- 6 picture had no prediction above 50%

Particle ID: GRIP\_3046\_0\_20\_1\_21916.png Probability: Ash: 46.64% Pollen: 15.88% Dust: 37.47%



Particle ID: GRIP\_3046\_0\_20\_1\_24026.png Probability: Ash: 49.46% Pollen: 49.78% Dust: 0.76%







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## Appendix:

#### Architecture of used CNN models

#### 3 type classification Model: "model"

#### 6 type classification

Layer (type)	Output Shape	Param #	Connected to	Layer (type)	Output Shape	Param #	Connected to
<pre>input_1 (InputLayer)</pre>	[(None, 64, 64, 1)]	0		input_7 (InputLayer)	[(None, 64, 64, 1)]	0	
conv2d (Conv2D)	(None, 64, 64, 58)	580	input_1[0][0]	conv2d_6 (Conv2D)	(None, 64, 64, 32)	320	input_7[0][0]
<pre>max_pooling2d (MaxPooling2D)</pre>	(None, 32, 32, 58)	0	conv2d[0][0]	<pre>max_pooling2d_6 (MaxPooling2D)</pre>	(None, 32, 32, 32)	0	conv2d_6[0][0]
conv2d_1 (Conv2D)	(None, 32, 32, 154)	80542	max_pooling2d[0][0]	conv2d_7 (Conv2D)	(None, 32, 32, 64)	18496	<pre>max_pooling2d_6[0][0]</pre>
<pre>max_pooling2d_1 (MaxPooling2D)</pre>	(None, 16, 16, 154)	0	conv2d_1[0][0]	<pre>max_pooling2d_7 (MaxPooling2D)</pre>	(None, 16, 16, 64)	0	conv2d_7[0][0]
dropout (Dropout)	(None, 16, 16, 154)	0	<pre>max_pooling2d_1[0][0]</pre>	dropout_3 (Dropout)	(None, 16, 16, 64)	0	<pre>max_pooling2d_7[0][0]</pre>
flatten (Flatten)	(None, 39424)	0	dropout[0][0]	flatten_3 (Flatten)	(None, 16384)	0	dropout_3[0][0]
input_2 (InputLayer)	[(None, 39)]	0		input_8 (InputLayer)	[(None, 39)]	0	
dense (Dense)	(None, 177)	6978225	flatten[0][0]	dense_12 (Dense)	(None, 128)	2097280	flatten_3[0][0]
dense_1 (Dense)	(None, 220)	8800	input_2[0][0]	dense_13 (Dense)	(None, 128)	5120	input_8[0][0]
concatenate (Concatenate)	(None, 397)	0	dense[0][0] dense_1[0][0]	<pre>concatenate_3 (Concatenate)</pre>	(None, 256)	0	dense_12[0][0] dense_13[0][0]
dense_2 (Dense)	(None, 1263)	502674	concatenate[0][0]	dense_14 (Dense)	(None, 1024)	263168	concatenate_3[0][0]
dense_3 (Dense)	(None, 3)	3792	dense_2[0][0]	dense_15 (Dense)	(None, 6)	6150	dense_14[0][0]
Total params: 7,574,613				Total params: 2,390,534			

Trainable params: 7,574,613 Non-trainable params: 0

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#### Architecture of used CNN models

#### **Pollen classification**

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 64, 64, 1)]	0	
conv2d (Conv2D)	(None, 64, 64, 32)	320	input_1[0][0]
<pre>max_pooling2d (MaxPooling2D)</pre>	(None, 32, 32, 32)	0	conv2d[0][0]
conv2d_1 (Conv2D)	(None, 32, 32, 64)	18496	<pre>max_pooling2d[0][0]</pre>
<pre>max_pooling2d_1 (MaxPooling2D)</pre>	(None, 16, 16, 64)	0	conv2d_1[0][0]
dropout (Dropout)	(None, 16, 16, 64)	0	<pre>max_pooling2d_1[0][0]</pre>
flatten (Flatten)	(None, 16384)	0	dropout[0][0]
input_2 (InputLayer)	[(None, 39)]	0	
dense (Dense)	(None, 128)	2097280	flatten[0][0]
dense_1 (Dense)	(None, 128)	5120	input_2[0][0]
concatenate (Concatenate)	(None, 256)	0	dense[0][0] dense_1[0][0]
dense_2 (Dense)	(None, 1024)	263168	concatenate[0][0]
dense_3 (Dense)	(None, 3)	3075	dense_2[0][0]
Total params: 2,387,459 Trainable params: 2,387,459 Non-trainable params: 0			

#### Ash classification

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 64, 64, 1)]	0	
conv2d (Conv2D)	(None, 64, 64, 32)	320	input_1[0][0]
max_pooling2d (MaxPooling2D)	(None, 32, 32, 32)	Θ	conv2d[0][0]
conv2d_1 (Conv2D)	(None, 32, 32, 64)	18496	<pre>max_pooling2d[0][0]</pre>
<pre>max_pooling2d_1 (MaxPooling2D)</pre>	(None, 16, 16, 64)	0	conv2d_1[0][0]
conv2d_2 (Conv2D)	(None, 16, 16, 64)	36928	<pre>max_pooling2d_1[0][0]</pre>
<pre>max_pooling2d_2 (MaxPooling2D)</pre>	(None, 8, 8, 64)	0	conv2d_2[0][0]
conv2d_3 (Conv2D)	(None, 8, 8, 64)	36928	<pre>max_pooling2d_2[0][0]</pre>
<pre>max_pooling2d_3 (MaxPooling2D)</pre>	(None, 4, 4, 64)	0	conv2d_3[0][0]
dropout (Dropout)	(None, 4, 4, 64)	0	<pre>max_pooling2d_3[0][0]</pre>
flatten (Flatten)	(None, 1024)	0	dropout[0][0]
input_2 (InputLayer)	[(None, 39)]	0	
dense (Dense)	(None, 128)	131200	flatten[0][0]
dense_1 (Dense)	(None, 128)	5120	input_2[0][0]
concatenate (Concatenate)	(None, 256)	0	dense[0][0] dense_1[0][0]
dense_2 (Dense)	(None, 1024)	263168	concatenate[0][0]
dense_3 (Dense)	(None, 2)	2050	dense_2[0][0]
Total params: 494,210			

Total params: 494,210 Trainable params: 494,210 Non-trainable params: 0

## Feature importance of metadata using SHAP-values



## Prediction of the test data using only metadata

3 split and subcategories



Pure 6 type classification



## Unsupervised learning on metadata (UMAP)

3 type classification

Ash classification

Pollen type classification

6 type classification









## Confusion matrices from training on only the metadata

qsub

qrob

corylus .

Actual label

3 type classification





2237

215

grim

Pollen type classification

6 type classification



## Unsupervised learning on metadata (t-SNE)



## **Contrast and Sharpness on pictures**

Before:



After:







