The Mercury HORNET: Ongoing Progress to Automatically Map and Classify Hollows

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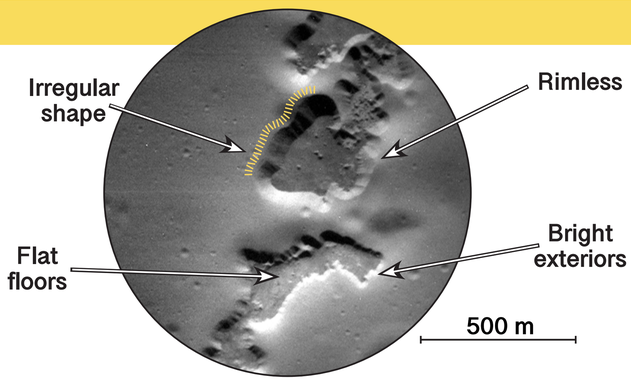
ABSTRACT #6001

Hollows on Mercury.

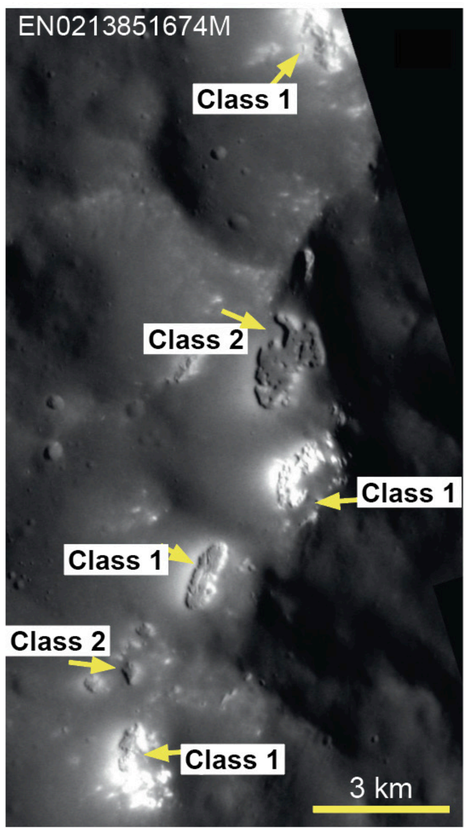
Hollows are some of the most interesting features on Mercury. These small, shallow depressions likely formed via volatile loss, and appear to be very geologically young[1–5].

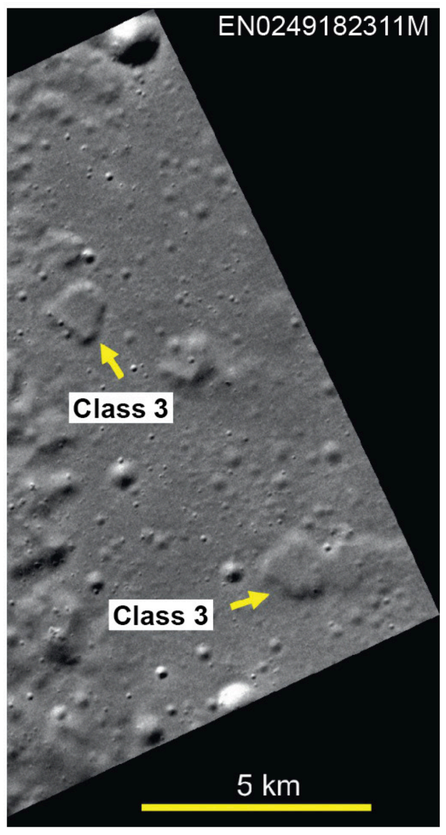
Today, important questions remain about the origin and evolution of hollows, and a detailed understanding of their **degradation state** and **distribution** can help address these questions.

We are taking an automated approach to identifying and classifying hollows by training a convolutional neural network based on the RetinaNet architecture[6], using a ResNet 50 backbone.



Degradation State: Clues to Evolution.



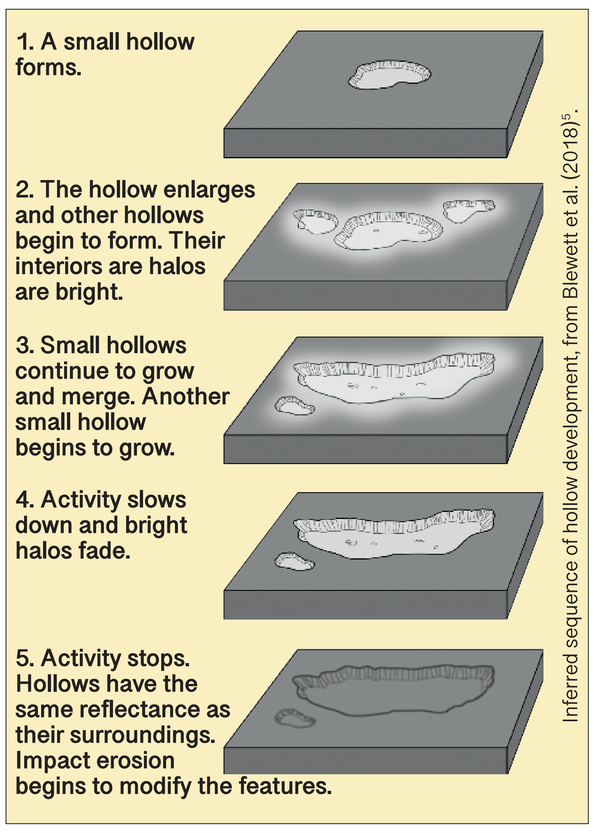


To date, three major classes of hollows have been observed.

Characteristic	Class 1	Class 2	Class 3
Reflectance	High	Neutral	Neutral
Morphology	Distinct	Distinct	Softened
Developmental Stage	Early / Active	Further along	Expired / Inactive

These classes may be linked to the developmental sequence of hollow formation. Open questions remain regarding when and why hollows evolve through these stages[7–10].

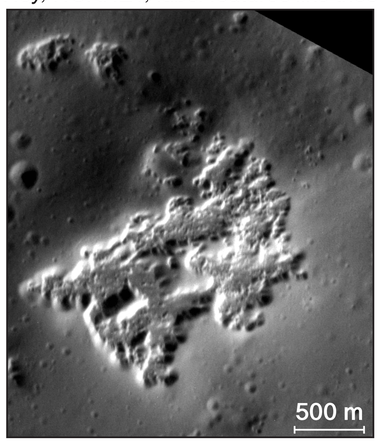
We are training the Mercury HOllows Retrieval NETwork (HORNET), to automatically detect hollows in MESSENGER images and classify their degradation states. This will enable a better understanding of hollow evolutionary sequences by analyzing the environments and



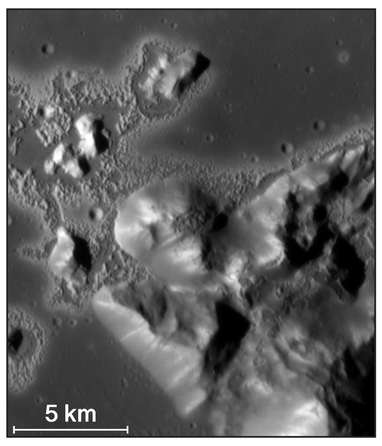
PILOT STUDY: Training the Mercury HOllows Retrieval NETwork (HORNET).

INPUT: Our pilot study demonstrated HORNET can automatically detect hollows in MESSENGER NAC images. Training sets included images of hollows and images of features that may look similar to hollows - like vents, pits, or small craters - but aren't.

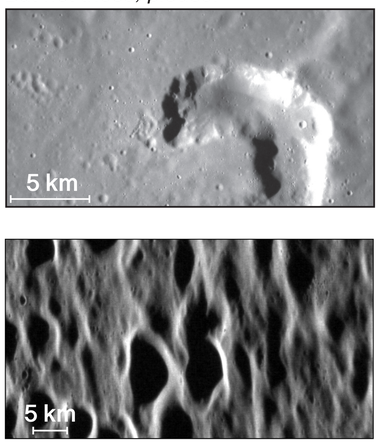
Hey, HORNET, label features like these as "hollows."



Or these.



But not these, please.

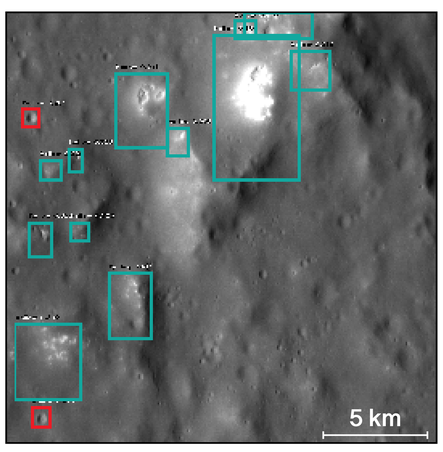


In this pilot study, HORNET was been trained on 69 NAC images and 1,012 labels. We used image augmentation during training to generate a total of 50,600 labels over 50 epochs* by varying:

- Rotation up to 90°
- Shear up to ±20%
- Scaling up to ±20%
- Chance of X & Y flip of 50%
- Contrast up to ±10%
- Brightness up to ±30%
- Hue up to ±3%
- Saturation up to ±5%

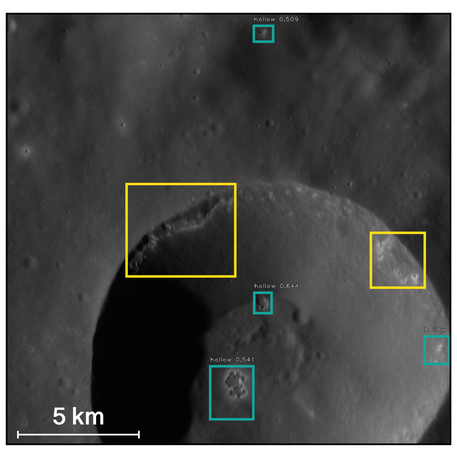
*In 50 epochs, the entire training dataset is passed through the neural network 50 times.

OUTPUT: Promising preliminary results yielded detections of hollows at a range of spatial scales (~10–100 mpp) and illumination conditions. The outputs are evaluated using recall and precision metrics, as defined below.



- A True Positive (TP) is where HORNET correctly identified a hollow.
- A False Positive (FP) is where HORNET labeled something else a hollow.
- A False Negative (FN) is where HORNET missed a hollow.

It's still learning.



An example output at Confidence Threshold (CT) = 0.2.
- **Recall = 0.85**
- **Precision = 0.81**

At lower confidence levels, more features are identified - including both hollows (TPs) and non-hollows (FPs). Recall goes up, precision goes down.

Outputs are evaluated by:

- Recall: The proportion of actual hollows that was identified (1.0 is optimum).
- Precision: The proportion of positive IDs that was actually hollows (1.0 is optimum).

An example output at Confidence Threshold (CT) = 0.5.
- **Recall = 0.58**
- **Precision = 0.90**

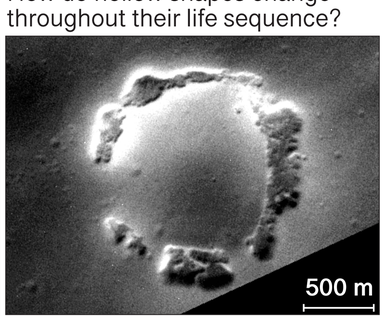
At higher confidence levels, HORNET is stricter in what it labels as hollows, so tends to miss some (FNs). Recall goes down, precision goes up.

A New and Improved HORNET: Ongoing Training Progress.

CLASS IDENTIFICATION: HORNET is being trained to not only identify hollows, but also to classify them as Class 1, 2, or 3. We can then analyse the local settings of each class to study hollow formation and evolution.

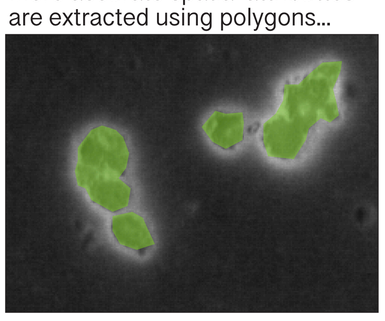
How do different classes relate to one another in a local setting?

How do hollow shapes change throughout their life sequence?

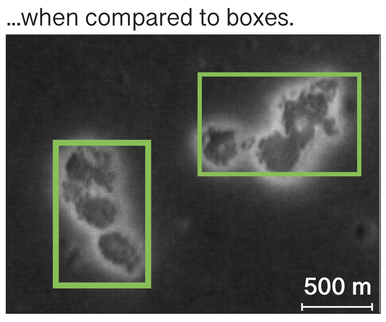


SHAPE TRACING: HORNET now includes segmentation capability for more accurate tracing and geometric measurements, like surface area, volume, elongation, and orientation. Segmentation is also best for change detection analyses.

More accurate spatial attributtes are extracted using polygons...



...when compared to boxes.



Applying the HORNET to MESSENGER and BepiColombo.

We are applying the HORNET to the entire MDIS dataset to scan globally for hollows. We will also be ready to infuse the Mercury HORNET with BepiColombo data by applying transfer learning principles, allowing for immediate and optimized progress in the global identification of hollows.

The automated identification of hollows has wide-reaching scientific applications:

Mapping, to understand processes driving volatile loss and hollow formation.

GLOBALLY:

- **What is the extent of the volatile-bearing layer?**
- **What is the extent of the proposed lag deposit that could limit volatile loss?**

LOCALLY:

- **Do hollows favor specific formation locations (e.g., Sun-facing slopes)?**

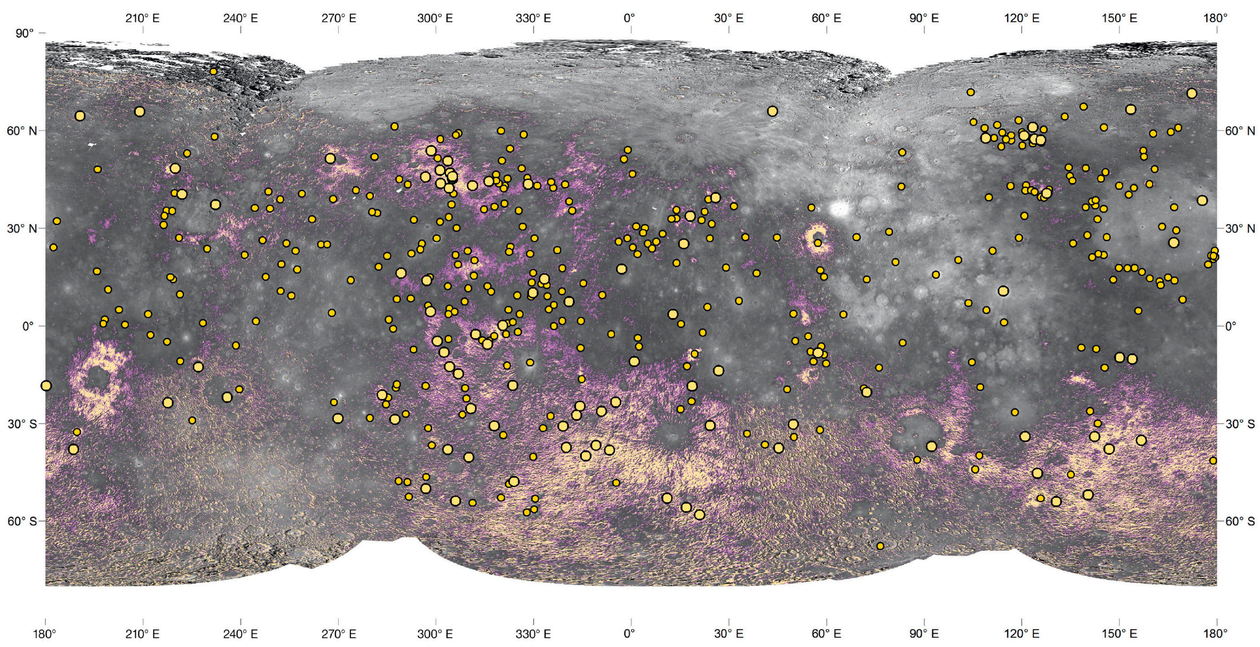


Figure: The global distribution of known hollows[3,5]. Peach-colored areas are low-reflectance material (LRM) and purple areas are low-reflectance blue plains (LBP)[11]. Large dots are hollows that plot within LRM or LBP and small dots are hollows located in neither LRM nor LBP at the scale of the global color images used for mapping.

Change detection, to understand growth sequences and rates of hollow formation.

- **What is the timescale of hollow development?**
- **Is hollow formation an active process on Mercury?**

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