

LROCNet: Detecting Impact Ejecta and Older Craters on the Lunar Surface

Emily Dunkel¹, Steven Lu², Kevin Grimes², James McAuley², and Kiri Wagstaff²

¹Jet Propulsion Laboratory

²Jet Propulsion Laboratory, California Institute of Technology

December 7, 2022

Abstract

NASA’s Planetary Data System (PDS)* contains data collected by missions to explore our solar system. This includes Lunar Reconnaissance Orbiter (LRO), which has collected as much data as all other planetary missions combined. Currently, PDS offers no way to search lunar images based on content. Working with the PDS Cartography and Imaging Sciences Node (IMG), we develop LROCNet, a deep learning (DL) classifier for imagery from LRO’s Narrow Angle Cameras (NACs). Data we get from NACs are 5km swaths, at nominal orbit, so we perform a saliency detection step to find surface features of interest. A detector developed for Mars HiRISE (Wagstaff et al, 2021) worked well for our purposes, after updating based on LROC image resolution. We use this detector to create a set of image chipouts (small cutouts) from the larger image, sampling the lunar globe. The chipouts are used to train LROCNet. We select classes of interest based on what is visible at the NAC resolution, consulting with scientists and performing a literature review. Initially, we had 7 classes: fresh crater, old crater, overlapping craters, irregular mare patches, rockfalls and landfalls, of scientific interest, and none. Using the Zooniverse platform, we set up a labeling tool and labeled 5,000 images. We found that fresh crater made up 11% of the data, old crater 18%, with the vast majority none. Due to limited examples of the other classes, we reduced our initial class set to: fresh crater (with impact ejecta), old crater, and none. We divided the images into train/validation/test set making sure no image swaths span multiple sets and fine tuned pre-trained DL models. VGG-11, a standard DL model, gives the best performance on the validation set, with an overall accuracy of 82% on the test set. We had 83% label agreement in our human label study; labeling was difficult as there is no clear class boundary. Our DL model accuracy is similar to human labelers. 64% of fresh craters, 80% old craters, and 86% of the none class are classified correctly. Predictions from this model will be integrated with IMG’s Atlas, allowing users to interactively search classes of interest. *<https://pds-imaging.jpl.nasa.gov> Copyright © 2022, California Institute of Technology. U.S. Government sponsorship acknowledged.

LROCNet: Detecting Impact Ejecta and Older Craters on the Lunar Surface

Emily Dunkel¹, Steven Lu¹, Kevin Grimes¹, James McAuley¹, and Kiri Wagstaff¹

¹Jet Propulsion Laboratory, California Institute of Technology *

Abstract

We train a deep learning model to classify images of the moon's surface obtained by the Lunar Reconnaissance Orbiter. Our model is able to detect craters, and distinguish fresh from old craters based on the presence of material spread outward by the impact that caused the crater. The model is more likely to miss a fresh crater than an old crater, but the overall accuracy is almost as good as a human. We plan to deploy our model on the NASA Planetary Data System, which is publicly available, to allow users to search lunar imagery based on content.

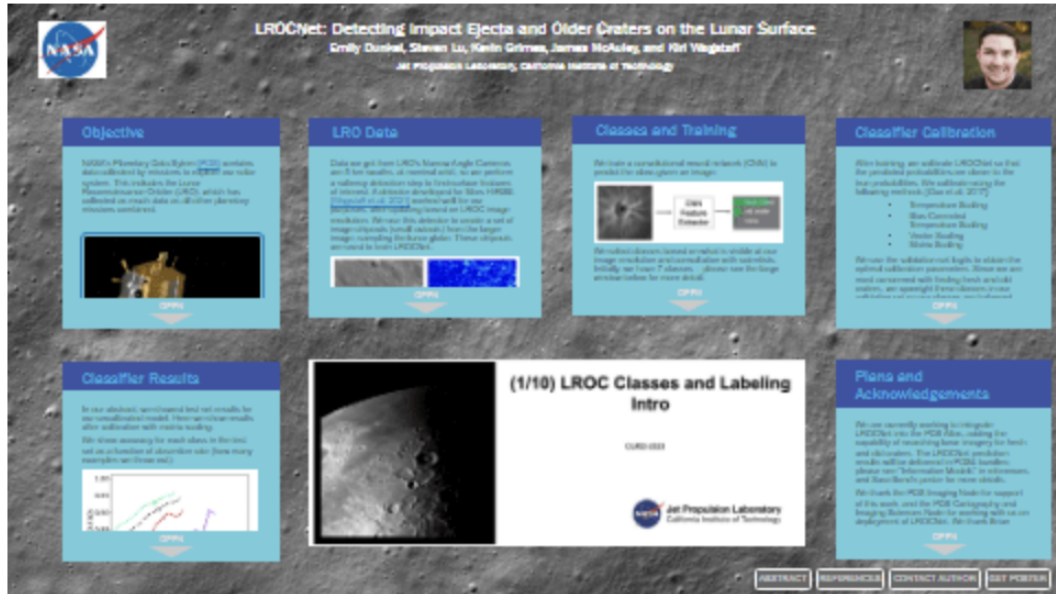


Figure 1: AGU Fall Meeting 2022 iPoster

1 Objective

NASA's Planetary Data System [1] contains data collected by missions to explore our solar system. This includes the Lunar Reconnaissance Orbiter (LRO), which has collected as much data as all other planetary missions combined.

Data is made publicly available by NASA/GSFC/Arizona State University [2][3][4][5][6].

*©2022 California Institute of Technology. Government sponsorship acknowledged.

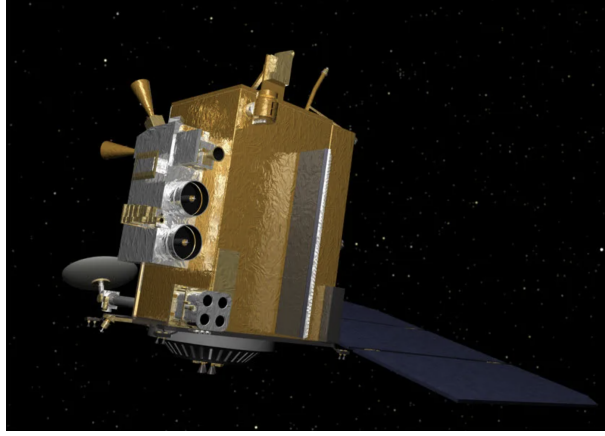


Figure 2: Rendering of LRO in Orbit (Credit: NASA/GSFC/ASU [7])

In the PDS Image Atlas, you can search for lunar imagery based on things such as latitude, longitude, and time, but you cannot directly search for say, *images with craters*. Thus, we develop LROCNet, a deep learning classifier for imagery from LRO’s Narrow Angle Cameras. Classifications from LROCNet will help us find images automatically that have new and old craters; we no longer need to manually search through the data.

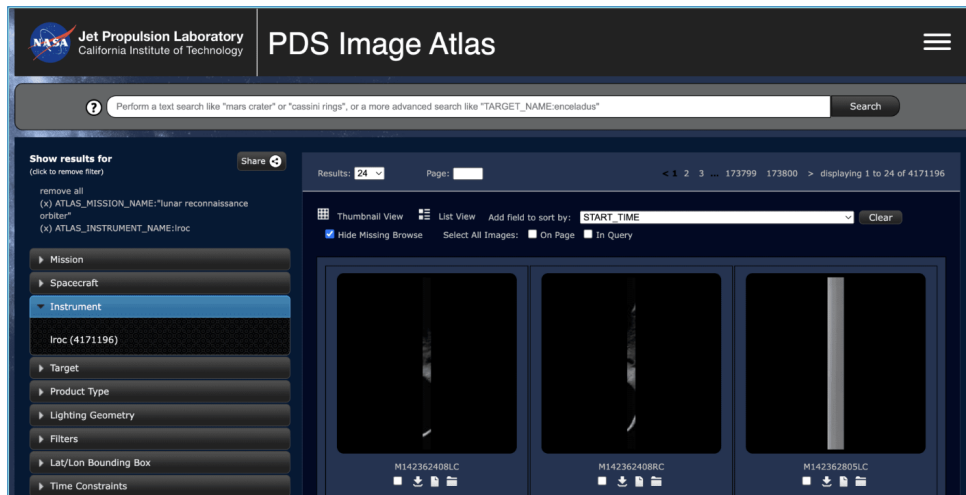


Figure 3: PDS Image Atlas Website [1]

Our approach to LROCNet builds on similar capabilities already created for Mars images at the PDS Imaging Node. Please see Steven Lu’s poster [8] to learn about models built using Mars rover data.

2 LRO Data

Data we get from LRO’s Narrow Angle Cameras are 5-km swaths, at nominal orbit, so we perform a saliency detection step to find surface features of interest. A detector developed for Mars HiRISE [9] worked well for our purposes, after updating based on LROC image resolution. We use this detector to create a set of image chipouts (small cutouts) from the larger image, sampling the lunar globe. These chipouts are used to train LROCNet.

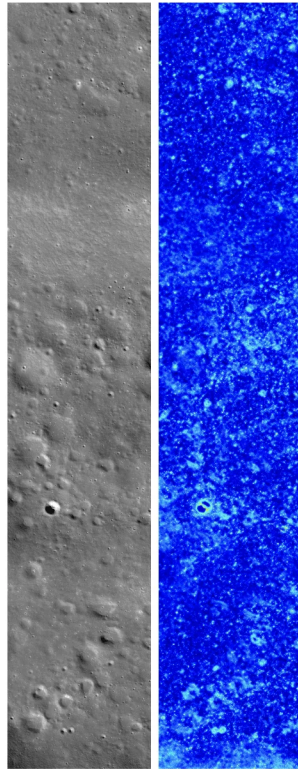


Figure 4: Example LROC Image (Credit: NASA/GSF/ASU) and Saliency Map

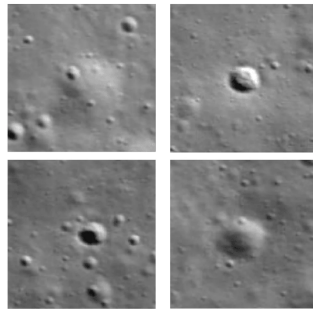


Figure 5: Example Chipouts from Larger Image. These are used to train LROCNet.

3 Classes and Training

We train a convolutional neural network (CNN) to predict the class given an image.

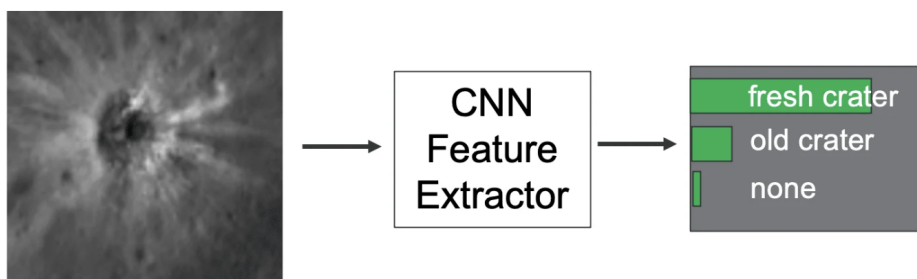


Figure 6: Class of Image is Predicted by LROCNet

We select classes based on what is visible at our image resolution and consultation with scientists. Initially, we have 7 classes (please see LROC.Labelling.Guide.pdf supplementary file for more detail)[10][11].

We labeled 5,000 images using the Zooniverse.org platform [12]. “Fresh crater” make up 11% of the data, “old crater” 18%, with the vast majority “none”. Due to limited examples of the other classes, we reduce our initial class set to these three.

We randomly divide images into train (73%), validation (12%), and test (16%) sets making sure there is no overlap of large image swaths between sets. We have made our data set publicly available on Zenodo [10].

We use PyTorch [13] to fine tune pre-trained Deep Learning models: Inception [14], VGG11 and VGG16 [15]. Data Augmentation is applied to the training set only and includes flips, rotation, brightness adjustment, and weighted sampling of classes (so we have an equal number of all three classes). We found VGG11 to perform best on the validation set data.

We show our training curve below:

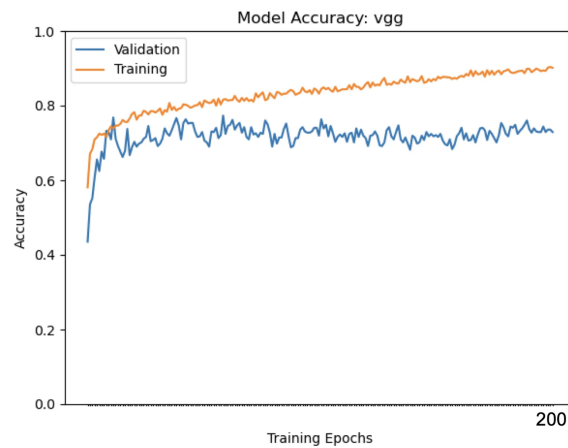


Figure 7: Training Curve

There is a gap between the validation and training set, which is because we weight balance our classes for the training but not for the validation set, otherwise the network will be weighted toward the “none” class. If we do not weight the classes in the training set, this gap disappears, as expected:

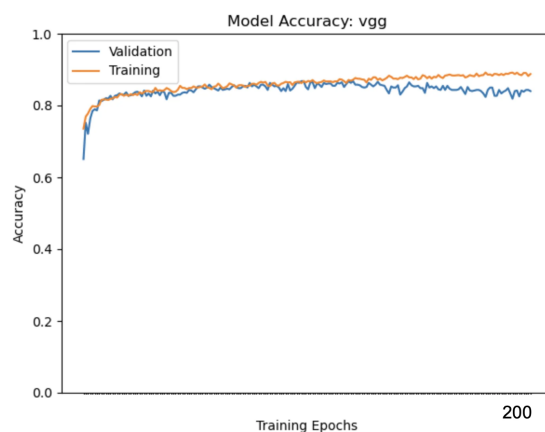


Figure 8: Training Curve Without Class Weighting

4 Classifier Calibration

After training, we calibrate LROCNNet so that the predicted probabilities are closer to the true probabilities. We calibrate using the following methods [16]:

- Temperature Scaling
- Bias-Corrected Temperature Scaling
- Vector Scaling
- Matrix Scaling

We use the validation set logits to obtain the optimal calibration parameters. Since we are most concerned with finding fresh and old craters, we up-weight these classes in our validation set so our classes are balanced, when obtaining the optimal calibration parameters.

Matrix scaling works the best, and gives an accuracy of 80% on the validation set:

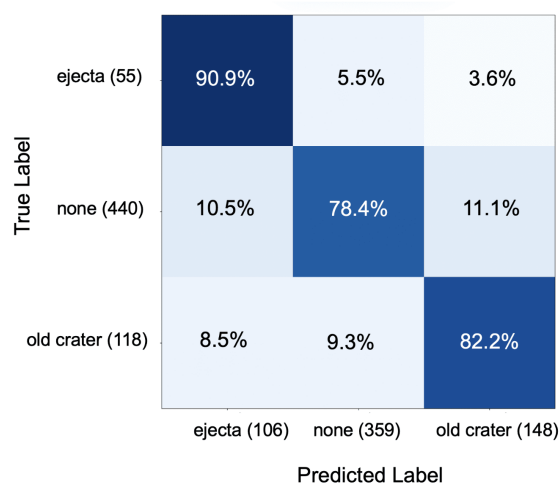


Figure 9: Confusion Matrix for Validation Set

The empirical probability versus predicted probability is shown below:

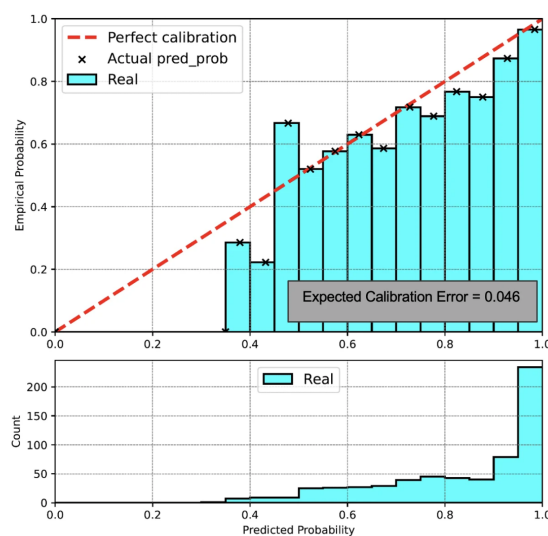


Figure 10: Empirical vs Predicted Probability for Validation Set

5 Classifier Results

In our official abstract (please see LROCNet_Abstract_EDunkel.pdf supplementary file), we showed test set results for our uncalibrated model. Here we show results after calibration with matrix scaling.

We show accuracy for each class in the test set as a function of abstention rate (how many examples we throw out):

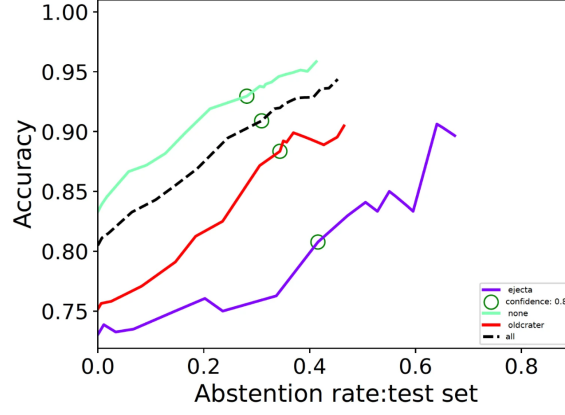


Figure 11: Class Accuracy versus Abstention Rate for Test Set

At a confidence of 0.8 (black circle in the graph), we see that we have 80% or higher accuracy for each class. When our model is deployed, we will only show examples at or above this confidence level.

Looking at accuracy versus abstention for training, validation, and test sets, we see these sets have similar performance:

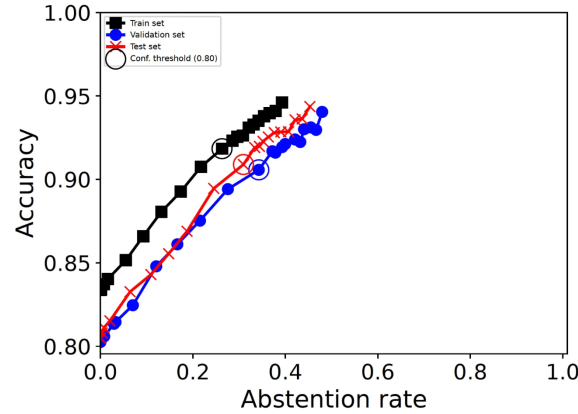


Figure 12: Dataset Accuracy versus Abstention Rate

At a confidence level of 0.8, we have over 90% accuracy for our datasets, and at 0 abstention rate, we still have over 80% accuracy.

We had 83% label agreement in our human label study; labeling was difficult as there is no clear class boundary. Our LROCNet model accuracy is similar to human labelers.

6 Plans and Acknowledgements

We are currently working to integrate LROCNet into the PDS Image Atlas, adding the capability of searching lunar imagery for fresh and old craters. The LROCNet prediction results will be delivered in PDS4 bundles [17, 18, 19]. Please Sara Bond's poster [20] for more details.

We thank the PDS Imaging Node for support of this work, and the PDS Cartography and Imaging Sciences Node for working with us on deployment of LROCNet. We thank Brian Milch for help with labeling, and Valentin Bickel and Lisa Gaddis for science support.

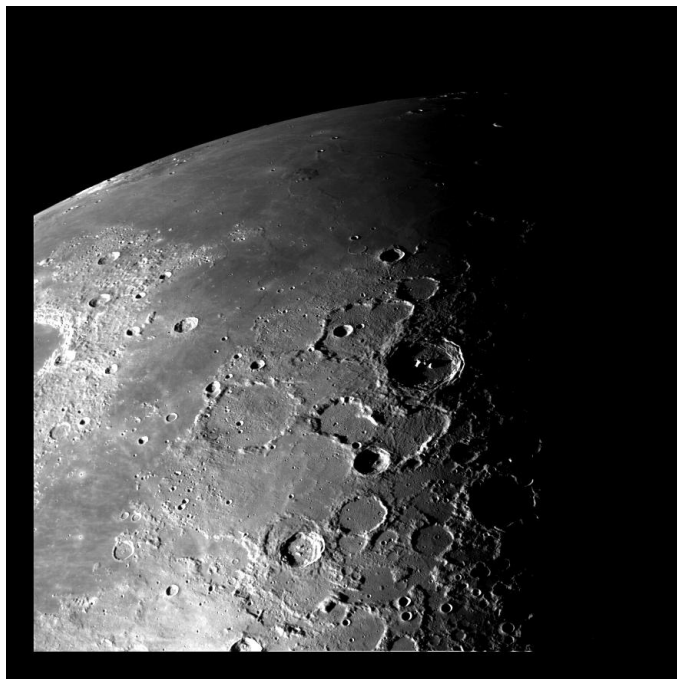
This publication uses data generated via the Zooniverse.org platform, development of which is funded by generous support, including a Global Impact Award from Google, and by a grant from the Alfred P. Sloan Foundation.

The research was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration (80NM0018D0004).

References

- [1] Planetary data system. <https://pds-imaging.jpl.nasa.gov/search>, 2022.
- [2] MS Robinson, SM Brylow, M Tschimmel, D Humm, SJ Lawrence, PC Thomas, BW Denevi, E Bowman-Cisneros, J Zerr, MA Ravine, et al. Lunar reconnaissance orbiter camera (LROC) instrument overview. *Space science reviews*, 150(1):81–124, 2010.
- [3] DC Humm, M Tschimmel, SM Brylow, Prasun Mahanti, TN Tran, SE Braden, S Wiseman, J Danton, EM Eliason, and MS Robinson. Flight calibration of the LROC narrow angle camera. *Space Science Reviews*, 200(1):431–473, 2016.
- [4] Prasun Mahanti, DC Humm, MS Robinson, AK Boyd, R Stelling, H Sato, BW Denevi, SE Braden, E Bowman-Cisneros, SM Brylow, et al. Inflight calibration of the lunar reconnaissance orbiter camera wide angle camera. *Space Science Reviews*, 200(1):393–430, 2016.
- [5] EJ Speyerer, RV Wagner, MS Robinson, DC Humm, K Becker, J Anderson, and P Thomas. In-flight geometric calibration of the lunar reconnaissance orbiter camera. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 39:B4, 2012.
- [6] MS Robinson. Lunar reconnaissance orbiter camera experimental data record. *LRO-L-LROC-2-EDR-V1. 0*, 2010.
- [7] Lunar reconnaissance orbiter. <https://www.lroc.asu.edu/>, 2022.
- [8] Steven Lu, Kiri Wagstaff, Emily Dunkel, Bhavan Vasu, Kevin Grimes, and Michael McAuley. Content-based search of large image archives at the PDS image atlas. In *American Geophysical Union Fall Meeting. AGU*, 2022.
- [9] Kiri Wagstaff, Steven Lu, Emily Dunkel, Kevin Grimes, Brandon Zhao, Jesse Cai, Shoshanna B Cole, Gary Doran, Raymond Francis, Jake Lee, and Lukas Mandrake. Mars image content classification: Three years of NASA deployment and recent advances. *Proceedings of the Association of Artificial Intelligence (AAAI) Conference on Artificial Intelligence*, 35:15204–15213, 2021.
- [10] Labeled data on Zenodo. <https://doi.org/10.5281/zenodo.7041842>, 2022.
- [11] Valentin Tertius Bickel, Charis Lanaras, Andrea Manconi, Simon Loew, and Urs Mall. Automated detection of lunar rockfalls using a convolutional neural network. *IEEE Transactions on Geoscience and Remote Sensing*, 57(6):3501–3511, 2018.
- [12] Zooniverse platform. [Zooniverse.org](https://zooniverse.org), 2022.
- [13] Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, and Edward Yang. Automatic differentiation in PyTorch. In *NIPS 2017 Autodiff Workshop: The Future of Gradient-based Machine Learning Software and Techniques*, 2017.
- [14] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1–9, 2015.
- [15] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.
- [16] Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q Weinberger. On calibration of modern neural networks. In *International conference on machine learning*, pages 1321–1330. PMLR, 2017.

- [17] PDS4 information model version 1.18.0.0. <https://pds.nasa.gov/datastandards/documents/im/v1/index1I00.html>, 2022.
- [18] Machine learning analysis submodel. <https://pds.nasa.gov/datastandards/dictionaries/index-1.18.0.0.shtml>, 2022.
- [19] PDS discipline namespace for machine learning products. <https://www.cosmos.esa.int/documents/6109777/9316710/M09+-+Wagstaff+--+2022-06-21-ML-submodel+%281%29.pdf/07decc8a-c296-0e04-6cb1-29cf9c56a6b1?t=1657277776443>, 2022.
- [20] Sara Bond, Kiri Wagstaff, and James McAuley. Machine learning is its own language: a common tool for the ML community. In *American Geophysical Union Fall Meeting*. AGU, 2022.



(1/10) LROC Classes and Labeling Intro

CL#22-2323



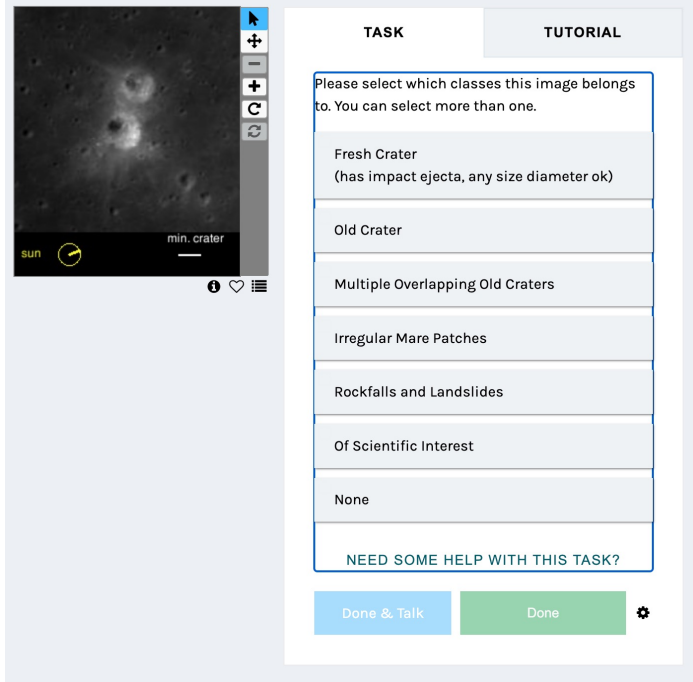
Jet Propulsion Laboratory
California Institute of Technology

© 2022 California Institute of Technology. Government sponsorship acknowledged.

(2/10) Used Zooniverse for Labelling

<https://www.zooniverse.org/>

LROC Imagery made publicly
available by: NASA/GSFC/ASU



The screenshot displays the Zooniverse web interface for a project titled "LROC Imagery". On the left, there is a preview of a lunar image showing a bright crater. Below the image, there are controls for zooming in (+) and out (-), a reset button (C), and a refresh button (refresh icon). A scale bar at the bottom left indicates "sun" and "min. crater". On the right, there is a "TASK" tab and a "TUTORIAL" tab. The "TASK" tab is active, showing a list of classification options. The instructions state: "Please select which classes this image belongs to. You can select more than one." The options are: "Fresh Crater (has impact ejecta, any size diameter ok)", "Old Crater", "Multiple Overlapping Old Craters", "Irregular Mare Patches", "Rockfalls and Landslides", "Of Scientific Interest", and "None". At the bottom of the task list, there is a link: "NEED SOME HELP WITH THIS TASK?". Below the task list, there are two buttons: "Done & Talk" and "Done", and a settings gear icon.

TASK **TUTORIAL**

Please select which classes this image belongs to. You can select more than one.

- Fresh Crater
(has impact ejecta, any size diameter ok)
- Old Crater
- Multiple Overlapping Old Craters
- Irregular Mare Patches
- Rockfalls and Landslides
- Of Scientific Interest
- None

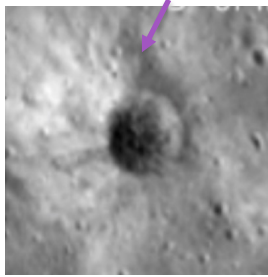
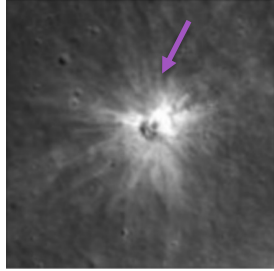
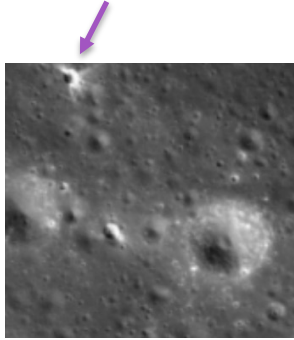
[NEED SOME HELP WITH THIS TASK?](#)

Done & Talk Done ⚙️

(3/10) LROC Classes

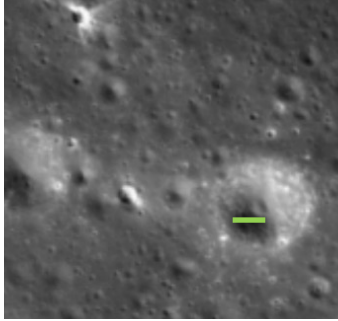
- We started with 7 classes:
 1. Fresh crater -- with impact ejecta, no size constraint
 2. Old crater
 3. Multiple overlapping old craters
 4. Irregular Mare Patches
 5. Rockfalls and landslides
 6. Of Scientific Interest – select very rarely
 7. None

(4/10) Fresh Crater (with impact ejecta) Examples



- Technically, the term *impact ejecta* means the material that is blasted out from the impact of a meteorite or the eruption of a volcano
- In this labeling setting, however, we also include the situation when the impact clears away overlying dust, exposing underlying surface
- Craters with impact ejecta are new, since there hasn't been enough time for the dust to clear

(5/10) Old Crater Examples



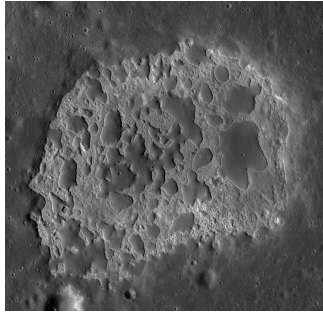
- After craters have been around a while, their impact ejecta clears
 - Old craters are sometimes referred to as degraded craters
- For our labeling purposes, we have more stringent requirements than just being a crater:
- **Crater diameter must be $\geq 1/10$ * width of image**
 - Size of green bar
- **Also, the rim must be visible for $3/4$ the circumference**
- So, if the crater is too degraded, we'll label it "None" instead of "Old Crater"
 - We just want to capture the larger craters w/ visible rings

(6/10) Multiple Overlapping Old Craters Example



- More than one old crater **overlapping** in image with diameter $\geq 1/10$ * width of image
 - At least two of the overlapping craters must fit the diameter requirement
- These images would also be classified as “old crater”

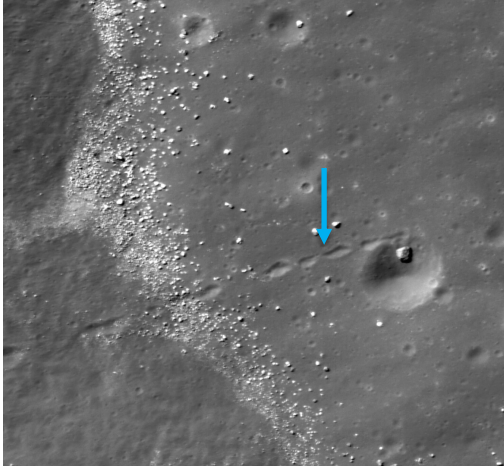
(7/10) Irregular Mare Patches Examples



Credit: NASA/GSFC/ASU

- Pronounced like: mare – ay
- Thought to be volcanic deposits!
- The moon has no active volcanoes, so these are evidence from long ago

(8/10) Rockfalls and Landslides Class



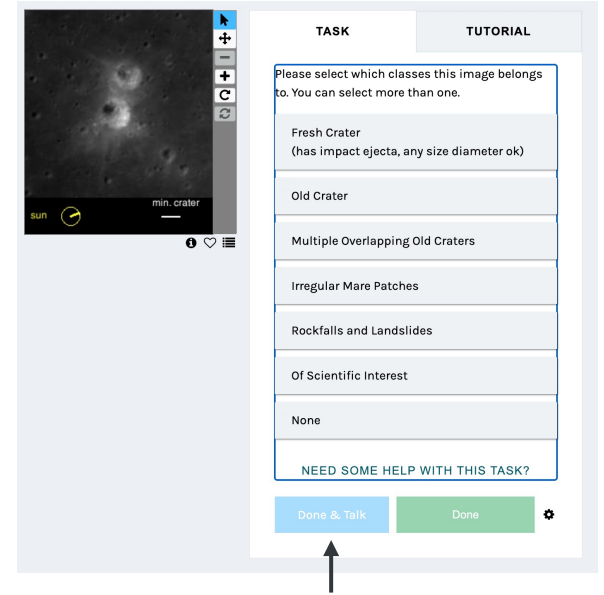
Credit: NASA/GSFC/ASU

- These aren't very likely, but if they are there, we want to label them!
- The arrow points to a boulder track
- For work on automated detection of these, please see: Valentin Bickel et al, "Automated Detection of Lunar Rockfalls using a Convolutional Neural Network", Trans on GeoScience and Remote Sensing, Vol 57, June 2019

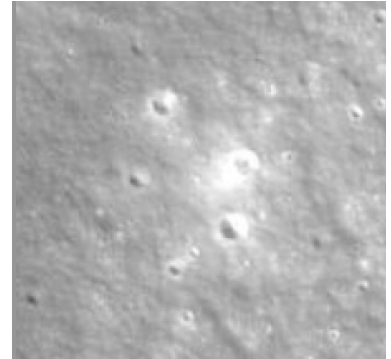
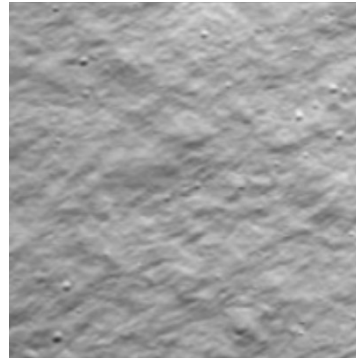
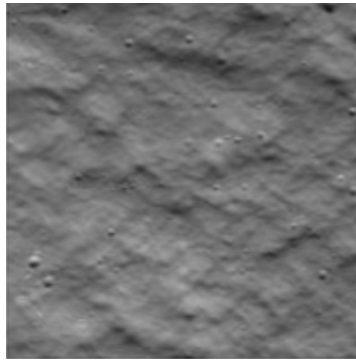
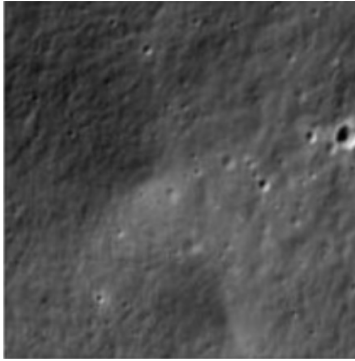
(9/10) “Of Scientific Interest” Class



- Can add comments in Zooniverse labeler by selecting “Done & Talk”



(10/10) “None” Class Examples



LROCNet: Detecting Impact Ejecta and Older Craters on the Lunar Surface

Emily Dunkel¹, Steven Lu¹, Kevin Grimes¹, Michael McAuley¹, Kiri Wagstaff¹

¹Jet Propulsion Laboratory, California Institute of Technology

NASA's Planetary Data System (PDS)* contains data collected by missions to explore our solar system. This includes Lunar Reconnaissance Orbiter (LRO), which has collected as much data as all other planetary missions combined. Currently, PDS offers no way to search lunar images based on content. Working with the PDS Cartography and Imaging Sciences Node (IMG), we develop LROCNet, a deep learning (DL) classifier for imagery from LRO's Narrow Angle Cameras (NACs).

Data we get from NACs are 5-km swaths, at nominal orbit, so we perform a saliency detection step to find surface features of interest. A detector developed for Mars HiRISE (Wagstaff et al.) worked well for our purposes, after updating based on LROC image resolution. We use this detector to create a set of image chipouts (small cutouts) from the larger image, sampling the lunar globe. The chipouts are used to train LROCNet.

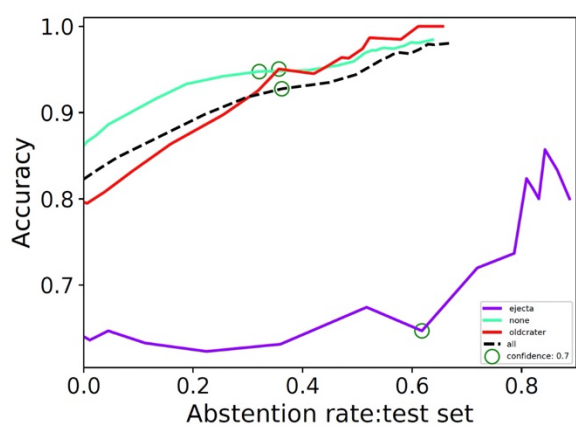
We select classes of interest based on what is visible at the NAC resolution, consulting with scientists and performing a literature review. Initially, we had 7 classes: *fresh crater*, *old crater*, *overlapping craters*, *irregular mare patches*, *rockfalls and landfalls*, *of scientific interest*, and *none*. Using the Zooniverse platform, we set up a labeling tool and labeled 5,000 images. We found that *fresh crater* made up 11% of the data, *old crater* 18%, with the vast majority *none*. Due to limited examples of the other classes, we reduced our initial class set to: *fresh crater* (with impact ejecta), *old crater*, and *none*.

We divided the images into train/validation/test sets making sure no image swaths span multiple sets. We fine tune pre-trained DL models. VGG-11, a standard DL model, gives the best performance on the validation set, with an overall accuracy of 82% on the test set. We had 83% label agreement in our human label study; labeling was difficult as there is no clear class boundary. Our DL model accuracy is similar to human labelers. In the figure, we show abstention rate, example chipouts, and test set confusion matrix; 64% of *fresh craters*, 80% *old craters*, and 86% of the *none* class are classified correctly. Predictions from this model will be integrated with IMG's Atlas, allowing users to interactively search classes of interest.

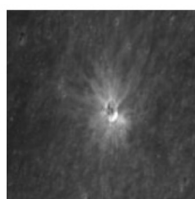
*<https://pds-imaging.jpl.nasa.gov>

CL#22-3842

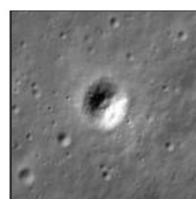
Copyright © 2022, California Institute of Technology. U.S. Government sponsorship acknowledged.



True label	Predicted label		
	ejecta (102)	none (509)	oldcrater (159)
	ejecta (89)	none (533)	oldcrater (157)
ejecta (89)	57	28	4
none (533)	35	459	39
oldcrater (157)	10	22	125



fresh crater



old crater