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Automated crater detection algorithms from a machine learning perspective in the convolutional neural network era

D.M. DeLatte [a,*], S.T. Crites [b], N. Guttenberg [c], T. Yairi [a]

[a] University of Tokyo, 7-3-1 Hongō, Bunkyō-ku, Tōkyō-to 113-8654, Japan

[b] Institute of Space and Astronautical Science/Japan Aerospace Exploration Agency, 3-1-1, Yoshinodai, Chuo-ku, Sagamihara City, Kanagawa Prefecture 252-5210, Japan

[c] Earth Life Science Institute, 2-12-1-IE-1 Ookayama, Meguro-ku, Tokyo 152-8550, Japan

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Abstract

Convolutional Neural Networks (CNN) offer promising opportunities to automatically glean scientifically relevant information directly from annotated images, without needing to handcraft features for detection. Crater counting started with hand counting hundreds, thousands, or even millions of craters in order to determine the age of geological units on planetary bodies of the solar system. Automated crater detection algorithms have attempted to speed up this process. Previous research has employed computer vision techniques with handcrafted features such as light and shadow patterns, circle finding, or edge detection. This research continues, but now some researchers use techniques like convolutional neural networks that enable the algorithm to develop its own features. As the field of machine learning undergoes exponential growth in terms of paper count and research methods, the crater counting application can benefit from the new research, especially when conducting joint interdisciplinary projects. Despite these advancements, the crater counting community has not yet adopted standard methods for automating the process despite decades of research. This survey enumerates challenges for both planetary geologists and machine learning researchers, looks at the recent automatic crater detection advancements using machine learning techniques (primarily in methods using CNNs), and makes recommendations for the path toward greater automation.

Keywords: Crater detection; Feature extraction; Automation; Machine learning; Convolutional neural networks; Mars

1. Introduction

Planetary geologists identified craters as a key to understanding planetary evolution in the 1970s (Crater Analysis Techniques Working Group, 1979). When a major geological event occurs (like a large meteorite impact), it wipes the surface geographic slate clean. Scientists may want to determine the age of that large crater or another area of geographic interest. By counting the number and size of the craters in the geographic unit, absolute age (on the Moon) or relative age (Mars, Mercury) can be determined.

Over time, researchers have developed various automated crater detection algorithms (CDA) which are intended to speed up the process of counting craters in new areas or to find smaller craters when higher resolution data is available. These automated methods largely track to the computer science methods of the time. Many computer vision techniques have been used and more recently, machine learning methods have become increasingly popular.

Although on Mars and the Moon craters are identified down to 1 or 2 km over the entire surface (Robbins,

* Corresponding author.
E-mail addresses: delatte@ailab.t.u-tokyo.ac.jp (D.M. DeLatte), yairi@ailab.t.u-tokyo.ac.jp (T. Yairi).

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2018a; Robbins and Hynek, 2012a) capturing the smaller craters, especially over a very large region, remains a daunting task. Additionally, as new data, especially higher resolution data, is provided to the scientific community, researchers re-evaluate the surface looking for additional scientific potential (analysis of secondary craters or boulder degradation).

While survey papers including some machine learning methods have been written on the topic of crater detection on planetary bodies (Patil and Kini, 2015; Salamunićcar and Lončarić, 2008a; Stepinski et al., 2012), none have yet covered the new machine learning approaches like the Convolutional Neural Network (CNN) based architectures of the past few years. Several other papers (Chung et al., 2014; Sawabe et al., 2006) compared a variety of methods on their dataset and included machine learning techniques among the number, but these papers came before the Convolutional Neural Network papers and techniques that are the focus of this review.

Adopting one or several CDAs across the community is a big challenge (Stepinski et al., 2012) as researchers differ in their techniques for counting. Many techniques used have been specific to a terrain region. A few papers (DeLatte et al., 2019; Silburt et al., 2019) have applied their method to a much larger and diverse set of terrain: ±30° latitude, 0–360° longitude.

While this paper focuses on the use of machine learning for crater counting, it fits into a larger body of work evaluating machine learning for space applications. For example, Kerner et al. (2018) assess Mars images from Mars Science Laboratory rover Curiosity with a neural network and evaluate each image's use for science. Nesvold et al. (2018) use machine learning to prioritize technology development for deflecting asteroids Nguyen et al. (2018) evaluate six classifiers for detecting debris disks. Shallue and Vanderburg (2018) use a CNN to detect exoplanets in multi-planet systems. This is a small sample of the journal research from only the past year and speaks to the enormous potential of machine learning to help recognize patterns and aid space science.

The major contributions of this work include: (1) categorization of the CNN techniques used on the Moon, Mars, and other planetary datasets; (2) description of potential benchmark datasets: combinations of annotation and image datasets that have been used in this research; (3) enumeration of challenges in using machine learning for crater counting; (4) discussion of promising techniques being developed in the machine learning community.

2. Research motivation & methodology

The goal of this survey is to understand where and how convolutional neural networks and other machine learning techniques have been applied to the crater detection and counting problem and consider future directions by looking to machine learning research in general. Accordingly, this work has two aims: (1) collect examples and evaluate a recent trend in using machine learning for crater counting, Convolutional Neural Networks (CNN), and (2) provide some context to both the machine learning and planetary geologist communities to help these communities understand the challenges of each discipline.

Applying machine learning, and specifically techniques using convolutional neural networks, to crater counting is a natural direction for this research, but for planetary geologists to collaborate most effectively with machine learning researchers, each group needs to understand the challenges of the other discipline.

This survey takes a close look at the use of convolutional neural networks in crater counting and puts that research in context by detailing other contemporary machine learning metrics. The focus of this study is papers that feature automatic crater detection using CNN and spanning 2015–2019 (and one early work from 2005). To accomplish the goals of the review, keywords such as "crater counting," "crater detection algorithm" were combined with "convolutional neural network," "support vector machines," "machine learning," and "deep learning" to find relevant papers. Further papers were found by reviewing citations within those papers.

In total, the authors identified thirteen published journal papers, book chapters, theses, and conference papers (four of which were Lunar and Planetary Science Conference abstracts) related directly to the use of CNNs in crater detection. Table 1 lists the criteria for including or excluding papers from this count.

2.1. Challenges

Collaboration between two disparate fields has both challenges and tremendous potential. By examining some of the key challenges for both planetary geology and machine learning, researchers can better understand where the synergies and friction points are in implementation. For example, a planetary data processing task that may seem monumental to a machine learning researcher may be easier for a geologist familiar with the tools and formats of satellite imagery. Implementing several existing machine learning architectures from Github repositories may be a herculean task or part of a typical day. By working together, these two groups can take advantage of existing strengths and focus on new challenges. A brief overview of the challenges are described in Table 2 and a larger discussion is included in 5.1.

A challenge to evaluating previous research in the field is the lack of similarity of datasets between papers. Even sharing statistics about the size of craters in meters, kilometers, etc. (as is common in planetary geology papers) could be somewhat misleading because of the difference in dataset resolution. (This issue is solved if the paper clearly

Table 1
Criteria for including and excluding articles from comparison.

Inclusion (if all criteria are met)	Exclusion (if any below criteria met)
Published 2000 or later Included crater detection or crater counting application Included experimental results	Non-English Conference papers whose contents were included in one of the journal papers (multiple publications by author)

Table 2
Challenges in Planetary Geology and Machine Learning.

Challenge	Details
Planetary geology	
Visualization challenges	Overlapping craters, degraded craters, and oddly shaped craters make it difficult to craft good "crater" features by hand. Light and shadows render differently in each type of data: visual, infrared, and elevation. It can be difficult for humans to accurately determine crater boundaries or coverage
Consistency and repeatability challenges	Experts disagree on image data interpretation. Prior research has shown that there is up to a 45% difference in how expert crater counters label the same regions (Robbins et al., 2014). With so much variability among experts' hand labeling of the same region, it will be difficult to create a single crater detection algorithm that is widely accepted. A machine learning algorithm would be consistent in the application of its feature detection, but for planetary geologists to agree on the best model would itself be a challenge. The treatment of secondary (craters formed after the primary impact, usually in an ejecta ring) and degraded craters would need to be chosen carefully
Machine learning	
Benchmark datasets	While annotations exist of various regions of planetary bodies, machine learning researchers entering the field do not initially have clear idea of the difficulty level of an area or interest. Currently, machine learning researchers choose datasets based on convenience, accessibility, and usability. Well formatted datasets on Github or another easily accessible, open source platform will be the first choice. Established datasets of agreed upon importance are needed, and those determinations can only be made by planetary geologists
Label criteria	Even with perfect ability to determine crater status, the choice of labels can significantly impact results. For example, if one crater is inside another, the inner crater can be hidden if the labels are crater/non-crater but visible using "crater rim" or "location/radius" parameters. Choices of this nature permeate the problem
Regularization and overfitting prevention	Large networks can "memorize" the training data, but these trained models most likely would not translate to a new region. Techniques like dropout (Srivastava et al., 2014) and data augmentation (Chollet, 2017) can help here, but there is no standard fix
Quality training data	The phrase "garbage in, garbage out" holds true here. High quality annotations enable a well-trained network. Training annotations that confuse the network with false positives and false negatives decrease the network's ability to correctly identify new craters. However, there are studies showing that neural networks are robust to significant label noise (Rolnick et al., 2017) and in some cases may actually generalize better with a small about of label noise. An important caveat is quality does not offset a lack of data
Transfer learning challenges	An algorithm that works very well for one type of terrain may be useless on another if features detected are too specialized to that terrain. Algorithms may not transfer or may transfer incompletely between planetary bodies. Furthermore, the type of loss used in training may be ill-suited if the density of features differs significantly between terrains
Tuning hyperparameters	Hyperparameters consist of the precise values selected for the architecture like: base architecture (full connected, U-Net, AlexNet, etc.), number of layers, number of filters, number of training epochs, learning rate, amount of training data, activation type for each layer, etc. Some have likened tuning hyperparameters to more art than science, and searching among various hyperparameter combinations efficiently is itself an area of ongoing research with methods like: grid search, Hyperopt (Bergstra et al., 2015), and a growing field of "automatic machine learning" (Jin et al., 2018; Zoph and Le, 2016)

states both the size in kilometers and the dataset resolution used.) A method that works on craters larger than 1 km using a particular dataset cannot necessarily be compared directly to another if they have different resolutions. Here, knowing the relative sizes of craters in pixels is useful for machine learning researchers. Additionally, challenges that plague some datasets are unique to that type. Digital Elevation Model (DEM) and Digital Terrain Model (DTM) data does not need to consider the angle of light, but the incidence angle is a vital consideration in visual and a moderate one in infrared. Thus, the reported detection percentages must be caveated with several clarifications: type of dataset (visual, infrared, DEM/DTM), size of the crater detection in pixels (converted from the range and resolution), type of instrument, resolution of the dataset, and angle of incidence.

3. Crater counting

3.1. History

Planetary geologists use crater counting on various solar system bodies to gain insight into the relative age of different geographic regions. An area contained within one geographic unit is chosen and the sizes of craters are grouped in logarithmic size bins. These techniques were initially developed for the Moon (Crater Analysis Techniques Working Group, 1979) and later expanded to other planetary bodies like Mars and Mercury (Hartmann and Neukum, 2001; Ivanov, 2006; Michael and Neukum, 2010; Neukum et al., 2001). Crater counts on the Moon can be anchored to absolute ages using returned Apollo samples. With an understanding of the population of projectiles, researchers can and do transfer the lunar chronology to other planets to get absolute age estimates (Hartmann and Neukum, 2001; Neukum et al., 2001). The community awaits samples returned from other bodies to anchor the ages of Mars and other planetary bodies, but standards for transferring the lunar chronology are accepted (Michael and Neukum, 2010).

A major challenge for obtaining chronology is some planetary bodies have properties that change crater appearance that are not directly related to age. Earth is the extreme example with craters being filled in by lakes, vegetation, or weathering over time decreasing the appearance of craters. (Even so, a terrestrial surface algorithm was developed to detect Earth craters (Li et al., 2017).) On Mars, weather can erode craters over time, causing degradation, but sometimes "fresh" looking craters are actually old. In these cases, the weathering may have exhumed the craters instead (Malin and Edgett, 2000). Airless bodies like the Moon or Mercury are less susceptible to this type of weathering, but this is a challenge that exists for human counters and automated algorithms alike.

3.2. Development: From hand counting to machine learning

Crater counting started with hand counting (Crater Analysis Techniques Working Group, 1979) and various techniques have been employed to optimize researcher time using existing technology. Expert hand labels are valued for their ability to discern the context of the terrain to distinguish between impact craters and other crater-like features. To speed up this time consuming process, many computer vision techniques have been investigated. For example, circle finding methods are used to evaluate DEM data (Luo et al., 2013). Recent research includes using object-based image analysis (Vamshi et al., 2016), handcrafted 3D features (Salih et al., 2017), rotational pixel swapping (Yamamoto et al., 2017), and terrain analysis (Zhou et al., 2018). The methods are contemporaries of machine learning methods that detect craters and other geographic features like decision trees, AdaBoost (Jin and Zhang, 2014; Martins et al., 2009; Wang et al., 2017), Support Vector Machines, and Convolutional Neural Networks. Handcrafting features lets researchers be very specific but the creation process is time consuming and prone to bias. Using machine learning methods like CNNs where the algorithm finds its own features lets the decision burden shift to human annotators who use their full visual experience to identify the craters. Instead of a human crafting a feature for detection, the CNN learns by the expert annotator's example. Hundreds or thousands of examples of craters and non-craters tune a model, which creates the features via the training process. CNNs can therefore pick out more complex features than what could be handcrafted. There is even potential for CNNs to need fewer pixels to identify a crater than a human, but this requires further research. (For this experiment, the human would annotate a higher resolution image, and the CNN could be trained on slightly or significantly lower resolution data.) However, even today, human counts remain the standard for detecting craters. While numerous techniques for aiding crater counters have been researched, none have yet been accepted by the broader community as a replacement for human eyes and analysis (Stepinski et al., 2012). In terms of evaluating terrain context, secondary craters, and potential clusters, no machine learning algorithm has fully addressed these issues (see Table 2 for challenges, see Table 3 and section 4 for CNN research).

3.2.1. Datasets

Existing planetary datasets vary in their ease of use for non-planetary specialists. This is an area ripe for collaboration: databases in non-standard image formats are challenging for machine learning researchers to use, but planetary geologists are familiar with the data. Digital Elevation Models (DEM) represent one promising data type. Recent machine learning work by Silburt et al. (2019) uses DEM data from the Moon and Mercury. Other DEM datasets are available for planets and dwarf planets: Mars (Fergason et al., 2018), Venus (Magellan Team, 1997), Mercury (Becker et al., 2016; Denevi et al., 2018), Vesta (Preusker et al., 2014), and Ceres (Preusker et al., 2016). DEM datasets are particularly valuable in this research due to their lack of encroaching shadows.

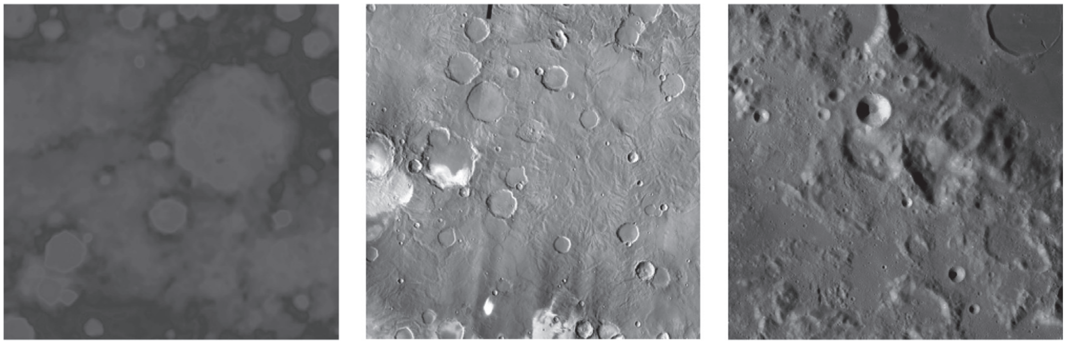
However, in DEM data, the complex terrain context is lost. Visual data and infrared data keep this context but are "noisier" in this regard as well. Visual and infrared images have shadows. Thus, craters at different latitudes appear vastly different due to the differing sun angle. There are myriad sources of visual and infrared images of planetary bodies in the solar system. A comprehensive resource for all types of data is the PDS Geosciences Node Orbital Data Explorer, which contains links to instrument data from Mars, Moon, Mercury, and Venus missions. Craters look different with each type of data; examples of DEM, infrared, and visible light imagery are in Fig. 1. (These regions are chosen only to illustrate the differences between the data types; the locations have no particular significance.)

Annotation datasets exist for various regions of the solar system. While full planetary coverage by a single

Table 3
List of crater counting papers that use CNN in their pipeline.

Paper title	Source type	Region studied	Datasets used	Resolution	Technique	Citation
Learning to Detect Small Impact Craters	Conference	Not specified	Not specified	Not specified	Neural network	Wetzler et al. (2005)
Automated Crater Detection on Mars Using Deep Learning	Journal	Mars	DEM (HRSC MOLA Blended DEM Global 200 m v2); Annotations RH2012	200 m/px	Segmentation (U-Net)	Lee (2019)
Segmentation Convolutional Neural Networks for Automatic Crater Detection on Mars	Conference, Journal	Mars ± 30° latitude, 0–360° longitude	Infrared (THEMIS Daytime IR); Annotations RH2012	231.55 m/px	Segmentation (Custom U-Net)	DeLatte et al. (2019, 2018a)
Lunar crater Identification via deep learning	Journal	Moon ± 30° latitude, 0–360° longitude	DEM (Lunar Reconnaissance Orbiter, Kaguya)	512 px/deg, 59 m/px	Segmentation (U-Net)	Silburt et al. (2019)
Automated Detection of Craters in Martian Satellite Imagery Using Convolutional Neural Networks	Conference	Mars ± 30° latitude, 0–360° longitude	Not specified	Not specified		Norman et al. (2018)
Automated Detection of Martian Craters Using a Convolutional Neural Network	LPSC abstract	Mars ± 30° latitude, 0–360° longitude	Infrared (THEMIS), Panchromatic (CTX); Annotations RH2012 (>1 km), Wener (0.1–1 km)	Not specified	Pretrained CNN, GoogLeNet-Overfeat	Benedix et al. (2018)
Lunar Crater Detection via Region-Based Convolutional Neural Networks	LPSC abstract	Moon	Hand labeled (200 tiles of 600x400 px); annotations, 270 craters>20x20px	Not specified	Localization + Classification (Faster R-CNN)	Emami et al. (2018a)
On Crater Classification Using Deep Convolutional Neural Networks	LPSC abstract	Moon	Lunar Reconnaissance Orbiter; annotations hand labeled	Not specified	Classification (VGGNet, GoogLeNet, ResNet)	Emami et al. (2018b)
Recognizing terrain features on terrestrial surface using a deep learning model	Conference	Earth	Color images; self annotated various Earth craters	Not specified	Classification (Faster R-CNN, ZF-net)	Li et al. (2017)
Automated detection of geological landforms on Mars using Convolutional Neural Networks	Journal	Mars	Mars Reconnaissance Orbiter, HiRISE, CTX	HiRISE = 0.3 m/px; CTX = 6 m/px	Multi-class CNN, SVM + HOG	Palafox et al. (2017)
Deep Networks: Applications, Interpretability, and Optimization	Thesis	Mars	Visual; Mars Express HRSC	12.5 m/px	Haar-initialized, CNN classifier (scaled down versions of LeNet, AlexNet, GoogleNet)	Lo (2016)
Crater Detection via Convolutional Neural Networks	LPSC abstract	Mars	Visual; Mars Express HRSC	12.5 m/px	Classification; fully connected CNN	Cohen et al. (2016)
Automated Crater Detection Using Machine Learning	Thesis	Mars	Visual; Mars Express HRSC	12.5 m/px	Classification; fully connected CNN; RandomOut	Cohen (2016)
Automatic Crater Detection Using Convex Grouping and Convolutional Neural Networks	Book	Moon	Visual; Lunar Reconnaissance Orbiter; annotations of hand labeled custom set	Not specified	Classification (Regions proposed with multi scale edge detection; candidates classified with CNN)	Emami et al. (2015)

counter or method is rare, they do exist. Table 4 lists several of these existing crater location databases. Researchers have used these and other catalogs to obtain ages on Mars (Pasckert et al., 2015; Platz et al., 2013) and the Moon (Hiesinger et al., 2010, 2000). Regional databases for Mars include: GT-57633 (Salamunićcar and Lončarić, 2008b), MA130301GT (Salamunićcar et al., 2011), and Nanedi Valles region (#h0905_0000) (Bandeira et al., 2010; Cohen et al., 2016). A regional database for the Moon is: LU78287GT (Salamunićcar et al., 2014).



(a) DEM, Mercury (b) Infrared, Mars (c) Visible, Moon

Fig. 1. Examples of DEM, infrared, and visible light images of craters. Craters pictured in (a) come from Mercury/Messenger (Denevi et al., 2018), (b) is infrared data from Mars/THEMIS (NASA Mars Odyssey/THEMIS Team, 2010), (c) is visible data from the Moon/Wide Angle Camera Global (Wagner et al., 2015).

Table 4
Full planetary body crater location databases.

Region covered	Size of craters detected	Original image data used for counting & type	Number of craters identified	Comments	Citation
Mars	$\geq$ 8 km ($\geq$5 km)	Viking 1:2M photomosaics	25,826 craters (42,283)	Paper notes use of $\geq$8 km for crater statistical analysis purposes and to exclude most secondary craters	Barlow (1988)
Moon	$\geq$20 km	Lunar Orbiter Laser Altimeter (LOLA), 64 pixels per degree DTM data	5158 craters	LOLA is an instrument on the Lunar Reconnaissance Orbiter (LRO) mission	Head et al. (2010)
Mars	$\geq$1 km	THEMIS (near infrared)	300,000+ craters	Largest database of Mars craters, hereafter: RH2012	Robbins and Hynek (2012a, 2012b)
Moon	200 km	Gravity Recovery and Interior Laboratory (GRAIL)	74 basins	Basins detected using changes in gravitational data	Neumann et al. (2015)
Moon	5–20 km	LROC Wide Angle Camera (WAC), 100 m per pixel, monochrome (643 nm) mosaic and DTM	22,746 craters	Extended the work of (Head et al., 2010)	Povilaitis et al. (2018)
Moon	$\geq$1-2 km	LRO WAC 100 m/px, LOLA, LOLA-Selene DTM 60 m/px, Kaguya 20 m/px Terrain Camera	2 million + craters	In review (as of January 2019), will be the largest database of Moon craters	Robbins (2018a, 2018b)

4. Application of machine learning

4.1. Convolutional Neural Network (CNN)

Convolutional Neural Network research has been active for decades. Recent advances and the availability of more powerful computational hardware has made CNNs a viable option for more types of image research in the past decade. Research has proven CNNs to be effective in two distinct image processing steps relevant to the crater counting pipeline, classification and segmentation (see below). The earliest found reference to a "neural network" applied to crater counting comes in Enke & Merline in 2005 (Wetzler et al., 2005), who deemed the technique not useful at the time. Much changes in ten years, especially in the machine learning community. The successful use of CNNs for classification started in 2015 (Emami et al., 2015) and 2016 (Cohen et al., 2016). Segmentation is being applied more recently (DeLatte et al., 2019; Silburt et al., 2019). Applying this research has the potential to reduce the time spent counting craters by hand, provide a more consistent application of a crater counting technique (labeling varies between experts and even between areas done by the same expert), and eventually provide a list of smaller craters without human counting as the techniques and resolution of imagery improves.

A CNN learns features important to analyzing the image by dragging a window (kernel) across the image. The kernel size refers to the number of pixels in a square window of interest. For example, a kernel size of 3 means that a sliding window of 3x3 pixels evaluates those nine pixels according to each of the filters. By using these square windows, a CNN preserves two-dimensional location information. The weights (numerical values) of a filter each determine one feature that the network can detect. CNNs learn features (filters) throughout the training process. In order to learn the best weights, a lot of training data is needed and additional data is necessary to validate the results.

The most popular data types in existing research are: visual/panchromatic, infrared, and elevation/terrain data.

The type of data has a significant impact on the study. Visual data is available at very high resolutions for the planetary bodies of interest and is a popular choice for hand labeling craters. Some of the highest resolution data is available for this type and there are several complete sets of images for different planetary bodies. The major downside to using visible light data for automatic crater counting is the variety of lighting conditions, which can make craters near the equator look very different than craters near the poles. There are also significant variations in lighting between datasets because of incidence angle. Infrared data, like the Mars THEMIS Daytime IR image set (NASA Mars Odyssey/THEMIS Team, 2006), partially addresses the lighting condition issue. Shadows are still visible, but the gradient is less than with visual data. Another data type, used successfully in Silburt et al. 2019, is digital elevation model or digital terrain model data. This data type has no issues with shadows as only the elevation data is reported for each pixel. With the regularity and symmetry of crater circular shapes, this type works very well for detecting craters; Silburt et al. 2019 also found many new crater candidates. (Yamamoto et al. 2017 also take advantage of this symmetry in their non-CNN method.) The biggest drawbacks to this type of data are it not being available for all planetary bodies and resolution limitations. To collect DEM data, a laser is bounced over the entire surface. The specialized instrument required is less common on planetary missions compared to imagers.

For any of these types of data used, researchers need to take care to include a representative sample of terrain types and levels of crater degradation in training if they are trying to apply their method over diverse terrain. Randomization of the separation of data into training, validation, and test sets is part of the solution. Across the Martian equatorial mid-latitudes (±30° N), for example, encompasses volcanic, highlands, and even a small amount of basin (Tanaka et al., 2014). It does not include polar, so methods trained in the equatorial mid-latitudes may not transfer as well to the polar region without additional training. Craters look visually different in those regions for both panchromatic and infrared data. Additionally, some of the typical methods of generating additional data (like rotating, flipping, etc.) images may not work as well when the features are learning to detect shadow patterns to distinguish between craters and mountains or boulders in visible and infrared data (DeLatte et al., 2019). Other techniques like sliding and resizing do work well to generate more data and rotations do aid in DEM data (Silburt et al., 2019).

A potential source of confusion for researchers new to the area is the similarity between paper titles and the overloaded use of key terminology. Seven separate papers have a variation of "automated crater detection…using convolutional neural networks" as part of the title (Benedix et al., 2018; Cohen et al., 2016; DeLatte et al., 2018a; Emami et al., 2018a, 2015; Norman et al., 2018; Palafox et al., 2017). The community needs to be more specific and unique with naming. Terms like "convolutional neural network," "automatic detection of craters," "novel detection algorithm," and their variations have become so ubiquitous that sifting through the differences is challenging. In early papers (Kim et al., 2005; Wetzler et al., 2005), neural networks are a novelty, but now with so many different types of CNN architectures available, more descriptive names are necessary to differentiate the techniques. Convolutional neural networks are used in a wide variety of algorithms that perform and work differently. Using a segmentation CNN (like U-Net) versus using Faster R-CNN involve CNNs in different places in the crater counting pipeline.

4.2. Use of CNN for crater counting

Machine learning, and specifically CNNs, can be used at various points within the crater counting pipeline. The pipeline consists of the steps between taking an image that contains craters and outputting a list of the crater locations.

While the descriptor "Convolutional Neural Network" helps identify machine learning papers, the use of a CNN model in a crater counting pipeline can vary greatly. Two major CNN research directions have emerged for the crater detection application: (1) classification methods (Fig. 2a, b) and (2) segmentation (plus localization, finding the relative pixel locations within the image of the craters) methods (Fig. 2c). The main difference from the CNN model's perspective between the categories is the scope of classification. In the first, the entire pre-processed (usually) square image is classified as a crater or non-crater image. In the second, a large image containing multiple craters (zero to hundreds) is passed in and each pixel gets classified as

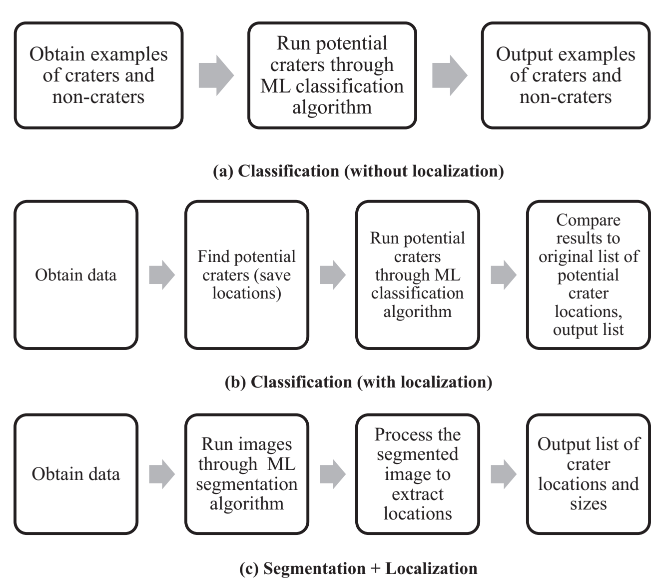


Fig. 2. Comparison in the use of CNNs (or machine learning) for classification vs segmentation: (a) Shows the classification pipeline, (b) classification with localization, (c) segmentation and localization.

belonging to a crater rim or not. (This means each pixel is designated as either a crater or non-crater pixel.) The rim crater pixels form rough circles or ellipses which can then be detected and used for localization.

Some CNN-based research classifies pre-processed images as crater or non-crater while other research segments the craters using a pixel-wise CNN classifier to create image maps of circles indicating where craters are and separately uses computer vision based circle finding methods to make a list of craters. The main difference between these two methods is the function of machine learning. Comparing results between classification and segmentation methods is challenging because it is important to compare metrics created by a similar process. In classification methods (after training), crater candidates must be pre-processed and rescaled, then each candidate is presented to the network for evaluation. This can be done by employing various computer vision techniques such as generating PHOG (Liu et al., 2012) or Gist (Yin et al., 2015) features, then passing the candidates through a CNN classifier. The location of the candidate examples must be known. The recall scores (number of matches divided by number of annotations) (Chinchor, 1992) tend to be extremely high, even 99% (Emami et al., 2018b), but there is a significant effort in preparing crater candidates. (This is very promising research, but the test set in that particular paper was limited). In segmentation + localization methods, the entire image is given to the algorithm, which splits it into chunks irrespective of the locations of craters, identifies crater candidates, which then can be post-processed to find the location. Traditional computer vision methods like template matching can be used to turn the newly identified circular shapes into a list of location and radius.

The feature identification step is treated differently in these two categories. Several of the classification methods used either existing image databases of crater and non-crater examples or created their own for the purpose of training the classifier. (One example that is less labor intensive in advance is to use a Region Proposal Network, as used in Faster R-CNN (Ren et al., 2016).) Then the crater examples are passed through the CNN-based classifier, which could have one of various architectures. Example architectures used in image classification include GoogLeNet, Alexnet, VGGNet, and ResNet.

This second segmentation category is less labor intensive in data preparation for the crater counter because during the training process, the features are automatically generated by the CNN. Further images can be presented as they are without the pre-processing. Once the model is trained, this is quick. Post-processing, however, can be time consuming because the computer vision template matching algorithms are comparatively slow. For example, in DeLatte et al. 2019, to evaluate a 30° by 30° THEMIS tile takes 2 min with a GPU, but the post-processing with the match template algorithm to obtain the full list of craters sized from 7 to 140 px in the tile (7680 × 7680 px) takes 20 min with a CPU.

While it is tempting to compare the percentages of recall between methods directly, results must be taken in context of terrain, crater size (in relation to pixels), network type, pre-processing complexity, and post-processing complexity. Comparing CNN classification methods versus segmentation methods recall percentages directly removes the vital nuances of the implementation complexities, scaling up challenges, and transfer learning potential. Another important distinction is understanding which terrain was used in training and test. A clear understanding of these differences allows future researchers to choose the best option for the scale of data they plan to evaluate.

Several researchers, including Emami et al. (2015), Cohen et al. (2016), and Palafox et al. (2017) evaluated the performance of CNN classifiers on planetary datasets. In Emami et al. (2015) and Cohen et al. (2016), resized and centered examples of craters and non-craters were used to train the CNN classifier. Palafox et al. (2017) use a multi-size classifier structure that could distinguish between examples of volcanic rootless cones and transverse aeolian ridges. (The same architecture was used to train separately for each geologic feature of interest.) While that research was not explicitly looking for craters, the same method could be used to find other geologic points of interest such as craters. For some applications, training a multi-class classifier can improve the recognition of objects of each class. This is theorized to be due to the additional training data available and ubiquity of some types of features (such as edges or shapes) (Emami et al., 2018b). Future research validating that for craters may inspire crater counters to more directly collaborate with boulder counters or groups interested in other geological features.

A promising lead for classification is to use a network first trained on other data. Benedix et al. (2018) and Norman et al. (2018) use a pre-trained GoogLeNet-OverFeat to detect craters. Emami et al. (2018b) pre-trained using ImageNet, then compare VGGNet, GoogLeNet, and ResNet, obtaining over 99% recall on their hand-annotated dataset. While very promising, this research is difficult to independently evaluate due to the lack of a baseline.

Emami et al. (2018a) continued research in the use of CNNs and implement Faster R-CNN for full pipeline crater detection. Although the scope of the craters used was limited, this research is promising and should be expanded to other annotation datasets and crater sizes. Unlike the methods that need handcrafted features, Faster R-CNN uses Region Proposal Networks to identify potential objects, which are then each resized and classified. Faster R-CNN outputs the location correction with the classifications, which removes the need for a post-processing step like template matching.

Segmentation methods, those that extract the edges of the target object, are used by both DeLatte et al. (2019) and Silburt et al. (2019). Both research groups used segmentation networks inspired by U-Net Ronneberger et al. (2015). DeLatte et al. (2019) evaluated different segmentation targets (edge-only and filled in crater) on a custom "Crater U-Net" to determine which had the best recall score for craters using infrared Mars images and the Robbins & Hynek annotations (RH2012) (Robbins and Hynek, 2012a). Silburt et al. (2019) use the original U-Net architecture to segment crater edges for lunar digital elevation model data and the Povilaitis et al. (5–20 km) (Povilaitis et al., 2018) and Head et al. (>20 km) (Head et al., 2010) annotation datasets. Both use a computer vision technique, template matching, to extract the crater locations and create the final list of craters. Silburt et al. (2019) also use transfer learning to apply their model to Mercury craters. The use of segmentation for crater counting has several advantages: the images do not need to be pre-processed into smaller "potential crater" images before being sent to the network and automatic localization is possible through the use of computer vision circle-finding methods. To perform localization, no bookkeeping needs to be done, and this method most closely resembles that of a human crater counter.

4.3. Other machine learning methods

Several other machine learning methods have been applied to crater counting, including Support Vector Machines (SVM) and decision trees. With most of these methods, the crater candidates must be localized prior to the machine learning algorithm being run. Accordingly, the locations are known a priori, but the identity of "crater" or "non-crater" is not. Several of these examples involve handcrafted features, especially in earlier research. Di et al. (2014) use Haar-like features and AdaBoost to classify craters in Mars Orbiter Laser Altimeter (MOLA) DEM data. Machado et al. (2015) use Haar textural features and a SVM classifier to detect craters in Kaguya Terrain Camera (evening illumination, 7.4 m/px) data of the lunar maria. Li et al. (2015) use binary decision trees to evaluate LOLA DEM data. These and other early machine learning research fall in the classification category with handcrafted feature development (PHOG, Gist, Haar).

5. Critique and further developments

5.1. Community needs baseline

Comparing the differences between algorithms remains a challenge due to the lack of an established baseline. The value of baseline datasets is found in both planetary geology and machine learning. In planetary geology, one region near the Apollo 16 landing site is used as a reference for lunar science and instrument calibration (Pieters et al., 2008) (pg. 251). In machine learning, datasets like MNIST (digit recognition, 0–9) and CIFAR-10 (images of common objects) are commonly used to compare classification algorithms. While these baselines provide value as points of comparison, one nuance is to ensure that they are not the only datasets used because optimizing for a single dataset limits transfer potential. (To address this, Kuzushiji-MNIST (Clanuwat et al., 2018), based on cursive Japanese characters, is proposed as an alternative to MNIST to expand the usage of those algorithms.) For crater counting, identifying a large, diverse baseline of image data and annotations would provide a better comparison of a network's potential across various types of terrain and planetary bodies.

Salamunićcar and Lončarić (2008a) proposed an open framework, but key elements have yet to be broadly adopted. However, several dataset combinations are better studied in crater counting and machine learning research. These regions are not necessarily better studied because of scientific value, but rather ease of use, especially if one researcher has published an easily accessible dataset. In a few cases (DeLatte et al., 2019; Silburt et al., 2019), the ±30° region was selected because the circular form of craters is preserved in the cylindrical projection. For example, (Benedix et al., 2018; DeLatte et al., 2019, 2018a; Norman et al., 2018) use THEMIS images (NASA Mars Odyssey/THEMIS Team, 2006) and RH2012 annotations (Robbins and Hynek, 2012a) are used with THEMIS in (DeLatte et al., 2019; 2018a). The Mars Nanedi Valles region, imaged by the Mars Express High Resolution Stereo Camera (HRSC) nadir panchromatic (#h0905_0000, 12.5 m per pixel) (Bandeira et al., 2010) is studied by numerous research groups (Bandeira et al., 2010; Cohen et al., 2016; DeLatte et al., 2018b; Ding et al., 2011; Urbach and Stepinski, 2009). On the Moon, annotations by Head et al. (>20 km) (Head et al., 2010) and Povilaitis et al. (5–20 km) (Povilaitis et al., 2018) are used for machine learning research (e.g., by (Silburt et al., 2019)).

A larger-scale candidate for an annotation baseline on Mars is the use of Robbins and Hynek Mars annotations (Robbins and Hynek, 2012a) and on the Moon, a combination of Povilaitis et al. (2018) (5–20 km) and Head et al. (2010) (>20 km), evaluated on ±30° latitude and all longitudes. Both datasets are well formatted, annotated by expert crater counters, and easy to use. Even if researchers are interested in other regions, also running their method on one or both of these datasets will allow real comparisons to be made between methods. An established set of crater baselines will provide the community with valuable comparisons for evaluating machine learning research.

5.2. Human in the loop

In order to work toward generally accepted increased automation, a phased autonomy approach could help. Currently, crater detection algorithms are primarily used only by their original developers and no standard exists for analyzing new image data or regions.

The current state of research is in Phase 2: Human in the loop (Table 5). There have been a few notable periods in the history of crater counting with massive shifts forward in thinking (i.e., adopting the cumulative crater curves to

Table 5
Increasing autonomy for crater counting with human in the loop.

Phases of autonomy	Characteristics	Requirements
Phase 1	Hand counted	Humans trained, agree on standard crater counting method
Phase 2	Human in the loop	Using established hand annotations, research many machine learning algorithms in use in other domains, output results to formats that can be loaded into programs like JMARS to evaluate, modify the predictions, and obtain ages
Phase 3	Full automation	Crater detection algorithms have gained sufficient accuracy and confidence among the planetary science community

evaluate Mars (Michael and Neukum, 2010)), and the community will likely need such a consensus to adopt either a single or a collection of automated algorithms. In the future, like how Craterstats is used to determine isochrons via various production functions (Michael, 2008), planetary geologists may be able to load one or an ensemble of several models for detecting craters in new data.

In order to move to the next stage of crater detection algorithms, development of code and software that uses one or more CDAs to generate a crater list that is then verified by humans may be the solution. The feedback from users could provide valuable additional training data. Over time, the algorithms could become tailored to the user if the corrections are used as additional training data. An example of what that could look like can be found in Fig. 3, which uses Object Process Methodology (Dori, 2011) to analyze what the crater counting pipeline with machine learning and a human in the loop could look like.

5.3. Future use of machine learning

Several of the trends in machine learning research such as the use of region proposal networks and classifiers (i.e., Faster R-CNN (Ren et al., 2016), Mask R-CNN (He et al., 2017)) and Generative Adversarial Networks (GAN) (Goodfellow et al., 2014) may have uses in the crater counting and localization problem. GANs in particular may be used to produce additional training data to avoid overfitting and the adversarial techniques approach may help improve transfer between different conditions. Although no journal papers have been published on these topics yet (that we could find), early results using techniques like Faster R-CNN have been published at the Lunar and Planetary Science Conference (Emami et al., 2018a) and other conference poster sessions, showing this is a promising direction within the community. With additional annotation datasets, more objects like boulders or lava tubes could possibly be detected using these techniques. Some research, such as (Palafox et al., 2017), already looks for multiple geological landforms on Mars, and Wang et al. (2017) looks for dark slope streaks. As more annotated databases become accessible and are formatted in ways that enable loading them into a machine learning algorithm, it is likely more research will go in this direction.

An interesting trend in machine learning is transfer learning, which can mean less specificity in training. A technique that has proved useful even in the crater counting

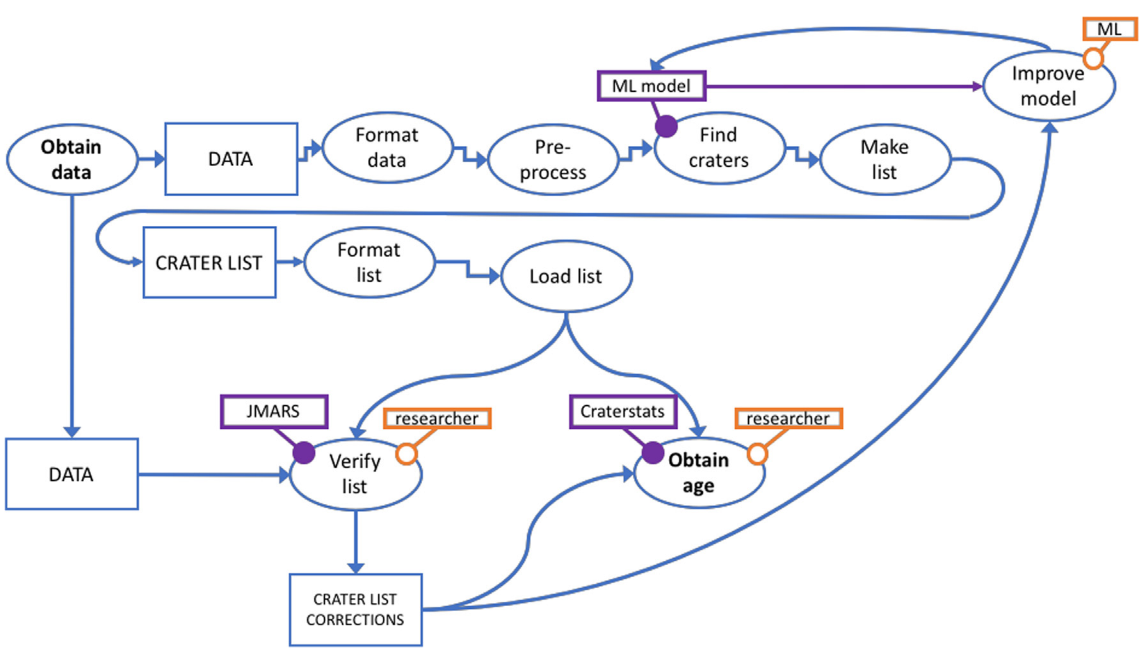


Fig. 3. Flow diagram showing the crater detection pipeline, using Object Process Methodology (Dori, 2011).

domain is using pre-trained networks as the base (trained on other images) and doing additional training with craters. This type of transfer learning will only improve as new networks are trained and represents an opportunity for scientists to use less data. Training from scratch requires more hyperparameter tuning. By using pre-trained or partially pre-trained networks, training time may be reduced and more types of network architectures can be used. For example, Norman et al. use GoogLeNet-OverFeat pre-trained with ImageNet to detect craters on Mars (Benedix et al., 2018; Norman et al., 2018).

Other opportunities include the use of more types of data simultaneously, i.e., hyperspectral data or DEM with visual data (Wang and Wu, 2019). Cloud computing offers an opportunity to work with these big datasets, especially for researchers who do not have access to super computers. Advanced deep learning architecture searches can be performed simultaneously with access to these remote resources.

6. Conclusions

Analysis of sensor and image data presents a valuable collaboration opportunity for machine learning researchers and planetary scientists. Planetary scientists can contribute their vast knowledge of dataset and formatting nuances. They can enable better collaboration by deciding which benchmark datasets are the best for algorithm comparison. Machine learning researchers can contribute expertise in image processing. Methods like segmentation and localization have been extensively developed in that community and are highly applicable to planetary analysis. Those who want their work to be used by the planetary science community can export their crater lists in formats friendly to the most popular crater analysis software, like JMARS (for verifying the list of craters) and Craterstats (for obtaining ages).

Since CNNs are used in several distinct ways, including segmentation and classification, throughout the crater counting pipeline, it is more important than ever to carefully define the methods. In order to improve the collaboration potential and enable machine learning researchers to build on existing research, key information needed in papers includes: technique(s) being used during each stage of crater identification and processing, annotation dataset (s) used to create training data, source of data, data augmentation methods, regions used for training, regions used for testing, hardware (i.e., specifications for Graphical Processing Units, Tensor Processing Units), training time, hyperparameters, and source code for repeatability.

Although there is not yet an accepted crater detection algorithm to replace human crater counters, the techniques presented represent tremendous progress to eventually reduce the time needed for new data to be processed. The recent trend of starting with pre-trained networks may ultimately represent the best solution, but until the community agrees on a set of benchmark annotations to be used for such training, exporting results to the formats of popular age dating programs and working with a human in the loop is the best short-term solution. Collaboration between planetary geologists and machine learning experts will enable great research and improvements in the way craters are detected.

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