LARGE-SCALE AUTOMATED DETECTION OF FRESH IMPACTS ON MARS USING MACHINE LEARNING WITH CTX OBSERVATIONS.

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Introduction: Fresh impact craters on Mars have been widely studied since the Viking orbiters reached Mars over 40 years ago [1,2]. Images from the Context Camera (CTX) onboard the Mars Reconnaissance Orbiter (MRO) [3] have covered 99% of the Martian surface and have enough resolution to identify fresh impacts whose blast zone is less than 100 meters in diameter. Identifying fresh impact craters by examining every CTX image is time-consuming, expensive, and likely infeasible with the full global set of over 100,000 images. In this study, we present a system that uses machine learning to detect and prioritize fresh impact candidates for review and follow-up.

Motivation: Cataloging fresh impact craters enables the refinement of current martian cratering rates [1,2]. These observations can also assist in investigations by InSight, a NASA discovery mission [4] that employs a Mars lander to study seismic signals and improve our understanding of the interior of Mars. Since fresh impacts provide known seismic ray paths through the interior of Mars [5], constraints on their times of formation can inform the interpretation of seismic activity observed by InSight. In addition, fresh impacts that reveal excavated subsurface ice can further our understanding of the distribution of subsurface ice on Mars [6] which is of interest for future Mars exploration. Finally, some less common fresh impacts exhibit ejecta that reveals subsurface material that is lighter than the surface and are currently under study [7,8]. Examples are shown in Fig. 1 and Tab. 1.

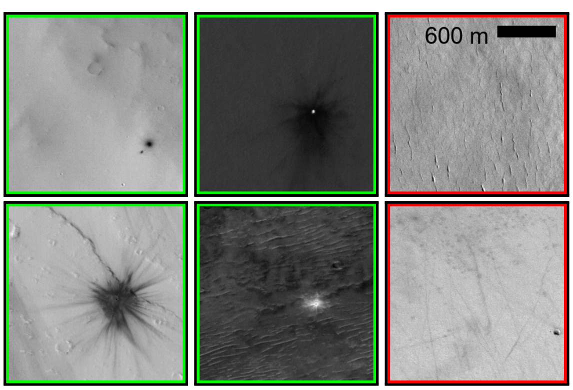

Figure 1: First column: typical fresh impacts; second column: impacts that reveal subsurface ice (top) and bright underlying material (bottom); third column: no fresh impact visible (top) and impact visible but not fresh due to lack of ejecta (bottom).

Fresh Impacts Data Set: To train the machine learning classifier, we first compiled all CTX cutouts centered on the locations of known fresh impacts [2] (positive examples) and a randomly selected set of cutouts without fresh impacts (negative examples). The cutouts are 300 pixels by 300 pixels and cover an area of $\sim$1.8 km by 1.8 km, which enables the detection of fresh impacts on the order of a few hundred meters with some surrounding context. For each known impact site, we obtained all overlapping CTX observations. We manually excluded observations that pre-date the impact (see Fig. 3 for an example) or in which the impact is not visible due to fading or poor localization. The result was a data set derived from 623 unique fresh impact sites with 1,858 positive and 4,973 negative examples (examples shown in Fig. 1; green = positive and red = negative).

ID	CTX ID	Date	Lat	E Lon
1	J04_046351_1869_XN_06N307W	2016-06-16	7.67	52.3
2	G19_025484_2254_XN_45N155W	2012-01-03	43.9	204.3
3	G23_027150_2238_XN_43N278W	2012-05-12	43.0	82.0
4	F16_041953_1887_XI_08N120W	2015-07-09	8.63	239.4
5	D13_032188_1719_XN_08S293W	2013-06-08	-9.5	192.8
6	F12_040371_1062_XN_73S113W	2015-03-08	-73.0	113.0

Table 1: CTX id, date, and location for examples in Figure 1.

Approach: We frame the fresh impact detection problem as a supervised learning problem in which an image is presented to a classifier and the output is the probability that the image contains a fresh impact. Deep learning models have been shown to perform remarkably well on visual classification tasks [9], including classification of Mars orbital imagery [10]. We employed the deep convolutional neural network Inception-v3, which was trained on millions of images [11]. We fine-tuned the parameters of this model with a process called transfer learning to adapt it to classify fresh impacts in grayscale CTX images.

Deployment: We devised a processing pipeline that scans across CTX images using a sliding window of approximately 1.8 km by 1.8 km, stepping by 0.9 km each time (see Fig. 2 for an example)

We divided the planet into sectors of approximately 10 degrees of longitude by 5 degrees of latitude to enable complete processing of all overlapping images in a given area before moving on to the next sector.

Visualization: For each candidate that is detected by the machine learning classifier, we assemble a complete sequence of all observations of the detected location

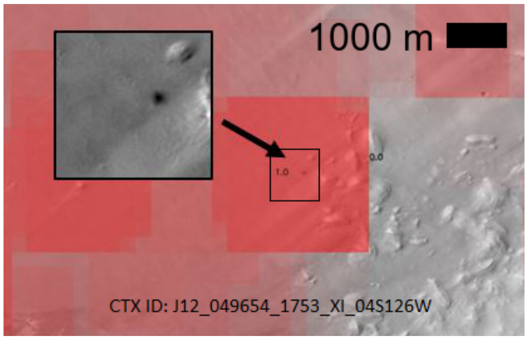

Figure 2: Sliding window detections: Higher degree of red indicates higher probability that the window contains an impact. In this example, the highlighted window has 1.0 probability.

over time (see Fig. 3). Each observation is accompanied by metadata that reports the original CTX id, date, L_s, and probability that the image contains a fresh impact, as reported by the classifier. Positive detections are surrounded by a green box. This sequence enables the identification of temporal constraints on the time of formation. In Fig. 3, the impact must have formed between November 2010 and June 2012. The black (negative) and green (positive) image borders draw the eye to the most constraining pair of images.

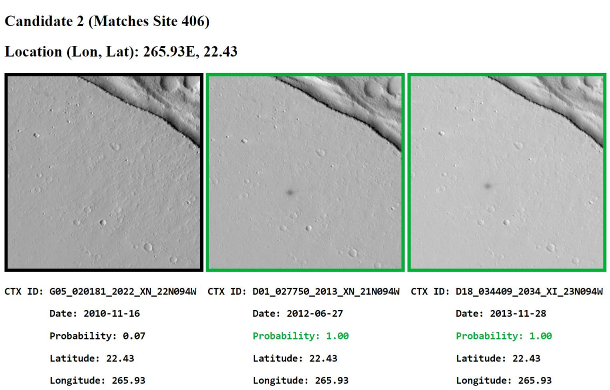

Figure 3: Example fresh impact candidate detected by the machine learning system (from the training set).

Preliminary Results: After training the classifier on the labeled examples, we ran it over an additional set of 455 CTX observations of known impact sites that were not included in the training set. The classifier found 25,715 potential fresh impacts (those with probability at least 0.85). The top 100 highest probability detections are shown in Fig. 4. We estimate that 87 of the 100 detections are valid impacts.

Currently, we are in the process of optimizing and testing our system to enable application to the global CTX catalog. Since the full data set contains more than 100,000 CTX images, we plan to utilize a supercomputer for this analysis.

Conclusions: Fresh impacts on Mars are of scientific interest, but they are difficult to manually detect given the vast amount of CTX data. We presented a machine learning system that can detect candidate fresh impacts from CTX observations and organize them for efficient human review. Our goal is to apply the system to the set of all CTX images, enabling a global search for fresh impacts. New detections can inform follow-up high-resolution images of a site of interest with the HiRISE instrument also on MRO to determine the true nature of each candidate [2] and accelerate scientific investigations into the seismology, geology, and history of Mars.

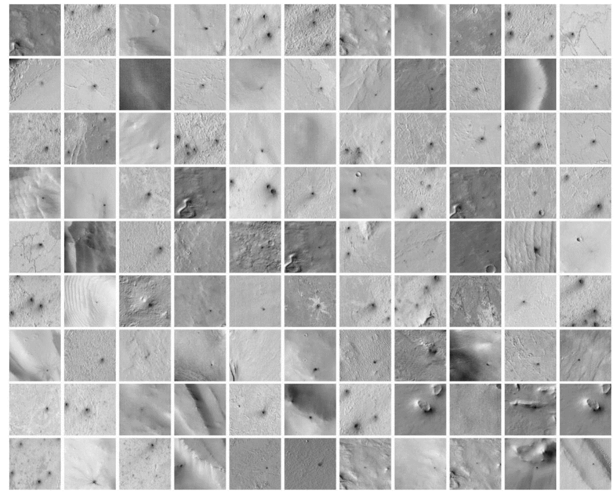

Figure 4: Top 100 highest probability detections from the 455 CTX observations of sites not used in training the system. We estimate there are 87 true positives in this image.

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