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Analysis of Lunar Impactors Using Deep Machine Learning and Neural Networks

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The problem of constructing a catalogue of lunar impact craters using deep machine learning and neural network methods is considered. A method was developed for analyzing satellite observations to reveal impact structures on the lunar surface. An analysis of the structure of impact objects and their relationship with slow asteroids was carried out. The created catalogue is planned to be used in the future to assess the content of mineral resources on the Moon.

Keywords: near-Earth asteroids, impact craters, neural networks

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Development of space technologies imposes special requirements for physical and chemical analyses of celestial objects [1]. This to the full extent refers to dynamic and planetary physical parameters of the Moon, in particular, to creating a complex digital selenographic model that gives an insight into formation of separate craters and any useful resources existing in them as a result of impacts with large meteoroids. To solve the problem of future space resource utilization, near-Earth asteroid substance utilization projects were developed. On the other hand, according to [2], utilization of asteroid substance delivered to the lunar surface might be a more technologically simple and cost-efficient process. Due to employment of the modern simulator algorithms [3,4], it has been found that, when the asteroid fall velocity was lower than 12 km/s, up to 40% of the impact object substance remains in the near-surface layer in a mechanically crushed state. Monitoring of impact events on the lunar surface performed by the LRO (Lunar Reconnaissance Orbiter) mission has shown that for a total of 222 new craters formed during 7 years a quarter of these impact events resulted from falling of „slow" asteroids that had a statistically average velocity of 10 km/s [5,6]. The lunar surface contains numerous impact craters occupying the largest part of it [7]. Lunar impact craters are related to five lunar geological periods, i.e. to the Pre-Nectarian, Nectarian, Imbrian, Eratosthenian and Copernican periods covering about four billion years. Their formation and evolution reflect the history of the Solar System interior [8]. Sixteen years of achievements in the lunar exploration projects (for example, the „Moon" missions and the „Apollo", „LRO", „Kaguya", „Smart-1" programs) made it possible to accumulate miscellaneous data, including digital images, digital elevation models (DEM) and lunar samples. Space image and DEM data analysis has identified many lunar impact craters [9], however, manual discovery subjectivity and automatic discovery restrictions with various types of data lead to significant differences in planetary physical properties of craters [10]. Modern explorations using manual processing methods studied only a set of simple craters and, thus, irregular-shaped and severely damaged craters, that could have been formed in early periods and could carry important information on the existence of asteroid-origin useful resources in them, were not accepted for processing [11]. Quantitative characteristics of craters have sufficiently wide diameter and scale ranges, and impact event traces on the surface differ significantly in shape due to crater overlapping or filling and have a variable and complex morphological structure. We have developed an automatic impact object discovery algorithms and software package [12] based on pattern recognition and machine learning (ML). Neural network model was generated and trained using ArcGIS software package. ArcGIS's Deep Learning module has wide model and material database for handling intellectual neural networks (INN). ArcGIS makes it possible to use the resulting trained INN model to examine other images. This software provides sampling and categorization of craters according to their visual characteristics. Lunar surface images obtained using the LRO mission were used to create a training sample. Figure 1 shows a manually drawn training material for the INN model, this material is used to train INN on searching an object on an image. Most typical craters with clearly defined walls are marked here. The INN model was trained during 40 epochs (about one hour), model training quality is estimated upon completion of this stage. We use an INN model that fulfils the classification task and also have a data package, in our case this is an image broken down into batches, then these batches fully pass the INN model —

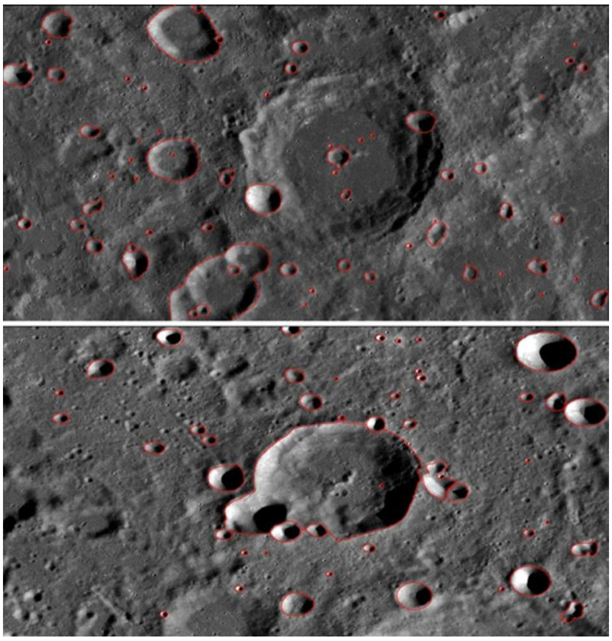

Figure 1. Most typical craters with clearly defined walls from the LRO mission data.

this is called one epoch. After passing one epoch, the neuron network activation function (AF) (based on the gradient descent) takes some value. With each epoch, taking into account weight setting, this value is better and better approximated to data. A small number of epochs (iterations) results in undertraining, while excessive epochs result in overtraining of the INN model. Overtraining is a situation when INN on some reason finds a pattern that should not exist and starts considering it during training. The optimum number of epochs may be achieved by a so-called „cut-off" function — it plots an activation function (AF) value curve, and as soon as the value deviates highly, the function will stop the training procedure, i.e. we can set 100 epochs manually and on epoch 40 the function will see that the AF value deviates from the target value and terminate the training process. The following method is used: a pre-formed AF and a random number of epochs are set initially, after cut-off the resulting AF value and a smaller number of epochs are selected.

Figure 2 left — a manually marked image fragment, right — marked INN based on training. As shown in the figure, it cannot be claimed that the INN model discovers the necessary objects accurately. The model cannot always highlight the fragments set in the training sample. Model undertraining is responsible for this problem. At the same time, objects not included in the training sample are highlighted, which indicates that the model understands what it should be trained to do. To improve the performance of this model, it was decided to increase the training sample size. A problem arises with small-diameter craters that are hard to be distinguished due to pixelization when the scale increases. These small craters may cause contradictions during INN training. Images with optimum resolution shall be selected and the absolute number of objects shall be highlighted on them. Training sample images shall differ in contrast, angle of rotation and number of objects on the image for the INN model to be more versatile. This work reviews 100 000 such objects (altimetric laser monitoring data obtained from the Clementine, Kaguya and LRO space missions are used) and samples impact craters by structural and planetary physical properties using deep machine leaning and neutron networking methods. Currently the findings are represented in the form of a preliminary version of an integrated fundamental digital selenographic catalog of impact craters distributed in corresponding categories. To achieve higher accuracy, we continuously increase both the number of images to be reviewed and the number of lunar craters. Thus, the final form of the catalog will be available later. The investigations established that the impact crater morphology depends on the crater's physical and chemical properties, and the crater depth and degradation with time don't depend on the surrounding surface relief. The latter statement makes it possible to determine the type of impact meteoroids that formed this crater: slow or fast. Slow meteoroids are those that had a velocity lower than 12 km/s during collision. If the impact object was slow, then up

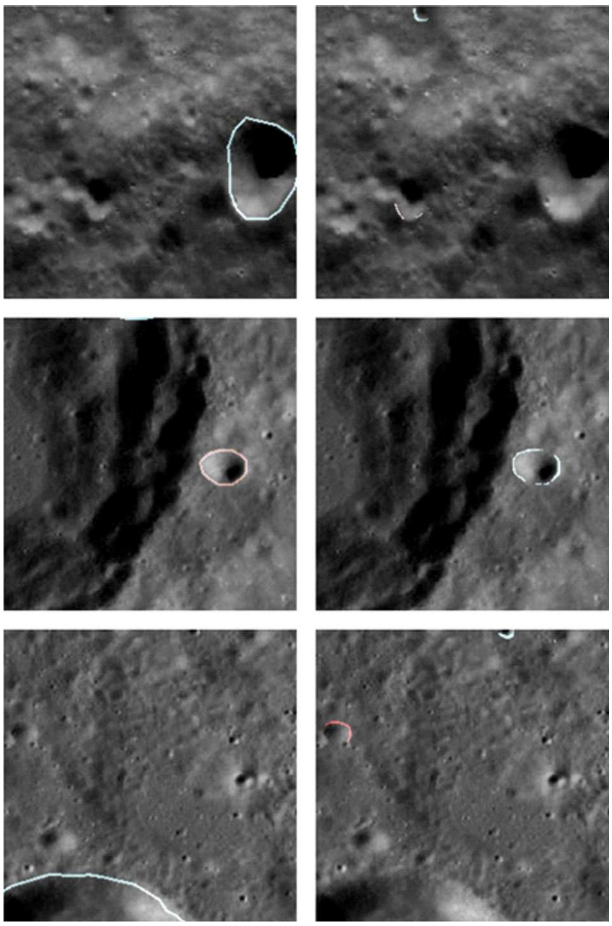

Figure 2. Comparison of manual sampling and INN sampling.

to 40% of its material composition lies close to the crater boundaries, thus, allowing future mining of useful resources accumulated near this object.

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Conflict of interest

The authors declare no conflict of interest.

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