



AUTOMATIC CRATER DETECTION AND CLASSIFICATION ON LUNAR SURFACE USING NEURAL NETWORKS

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ABSTRACT

Secondary craters are formed from the impact of the ejecta expelled during the primary crater formation. They contaminate the process of crater counting through CSFD (Crater Size-Frequency Distribution) method leading spuriously high surface age estimation. Therefore, it is necessary to eliminate them beforehand. So far, secondary crater detection has been done through manual or rule-based automatic methods. This study proposes an approach to automatically discriminate a secondary crater from the primary ones using Neural Network framework. The investigation area surrounds the Orientale impact basin, i.e., region covering an area of about six radii from the rim of Orientale, with the help of DEMs obtained from TMC-2 instrument onboard Chandrayaan-2. The proposed methodology consists of selecting the region of interest, the one which overlap with secondary crater database (surrounding Orientale impact basin) provided by [1], preparing the dataset and exporting it into YOLO format and then finally training a neural network architecture, YouOnlyLookOnce (YOLO) version 8 [2]. To test the approach, the detected craters are checked with the already reported secondaries by [1]. The new detections are verified by rule-based approach, by extracting the morphological parameters and observing the spatial distribution encompassing chain or cluster arrangements. The objective of this study is to prepare global map of secondaries on lunar surface utilizing TMC-2 data set.

OBJECTIVES

Primary objective: Develop a framework which can help in crater detections as well as classification using Neural Network architecture.

Secondary objective: Prepare a global map of secondaries on the lunar surface utilizing TMC-2 data set.

STUDY AREA

The investigation area surrounds the Orientale impact basin, i.e., region covering an area of about six radii from the Orientale basin rim crest (~ the Cordillera ring about 930km in diameter). The study area comprises about 63% of the entire lunar surface area. Guo et al., 2018, provided with a secondary crater catalogue for the same area surrounding the Orientale basin. And so, the idea behind selecting Orientale basin as study area was to utilize this secondary crater catalogue for our work.

TECHNIQUES AND ALGORITHMS

In this study, we are using the DEM (Digital Elevation Maps) data strips obtained from TMC-2 payload onboard Chandrayaan-2 [3], which overlaps with our region of interest. For Ground-truth, we used the Robbins crater catalogue, which consists of roughly 1.3 million lunar impact craters [4] and the secondary crater catalogue surrounding the Orientale impact basin provided by [1], which consists of about 2728 secondaries. To build the dataset we extracted 208 random tiles of 512 x 512 pixels from the ROI, then we overlapped the labels obtained from Robbins and Guo's databases in these tiles. The crater catalogue provided by Guo et al., had the longitude system of [-180,180], we changed it to [0,360] reference. As for network training, an Ultralytics implementation of YouOnlyLookOnce (YOLO) version8 [2] is used. The work is done in Python 3.10.5 and with the help of GIS software – QGIS.

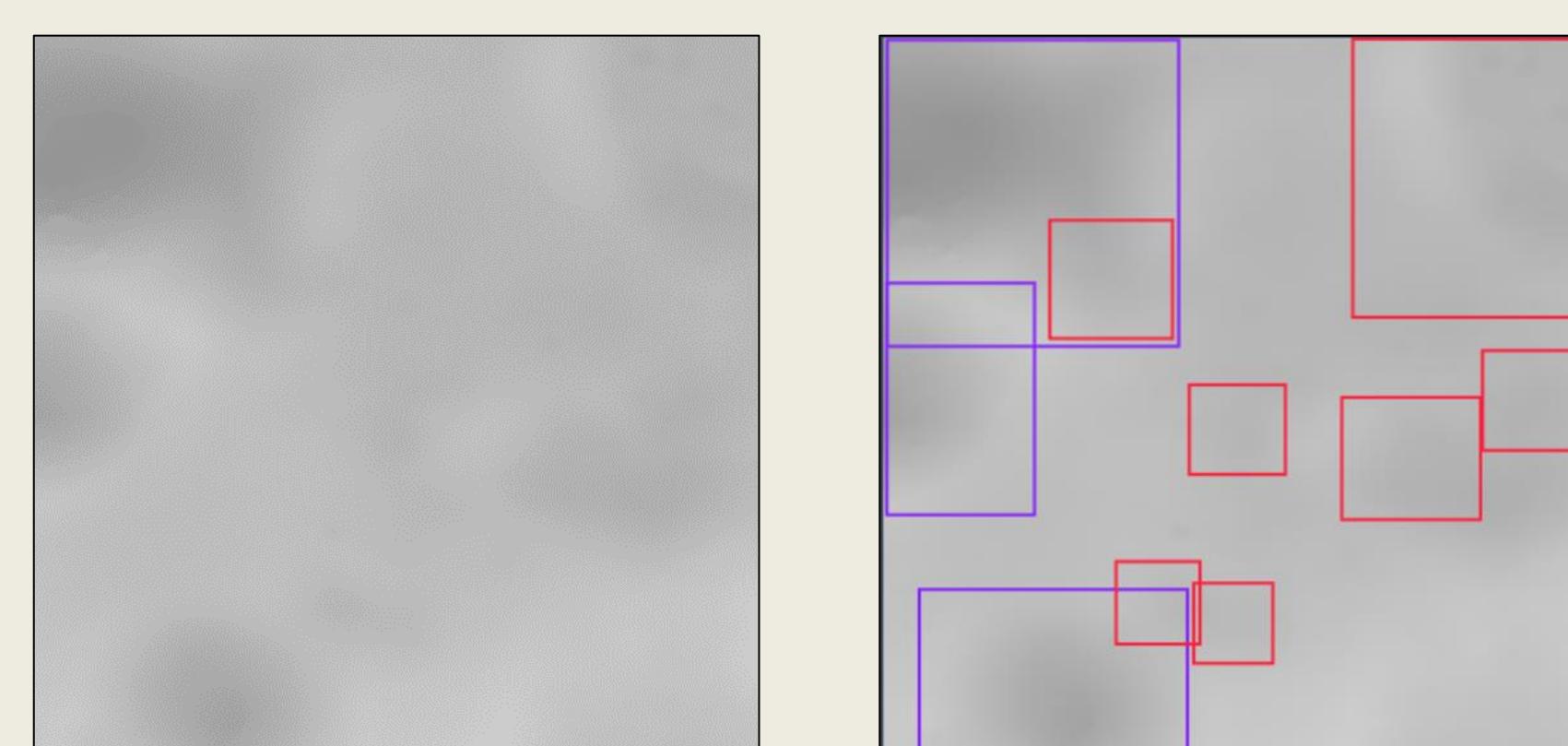


Figure 1. Input image and corresponding ground truth with YOLO annotations (Red shows Primary craters and Blue shows Secondary craters)

RESULTS AND DISCUSSION

The technique used comprises of training two neural-net models, YOLOv8n and YOLOv8s, which has approximately 3.2 million parameters and 11.2 million parameters, respectively. Both the models are trained for 50 epochs. Evaluation metrics used here are : *Mean Average Precision (mAP)* which is useful in multi-class object detection scenarios to provide a comprehensive evaluation of the model's performance and *Classification Loss (cls_loss)* which measures the accuracy of predicting the correct category of the objects within the bounding boxes. Lower *cls_loss* points towards a more accurate classification of objects.

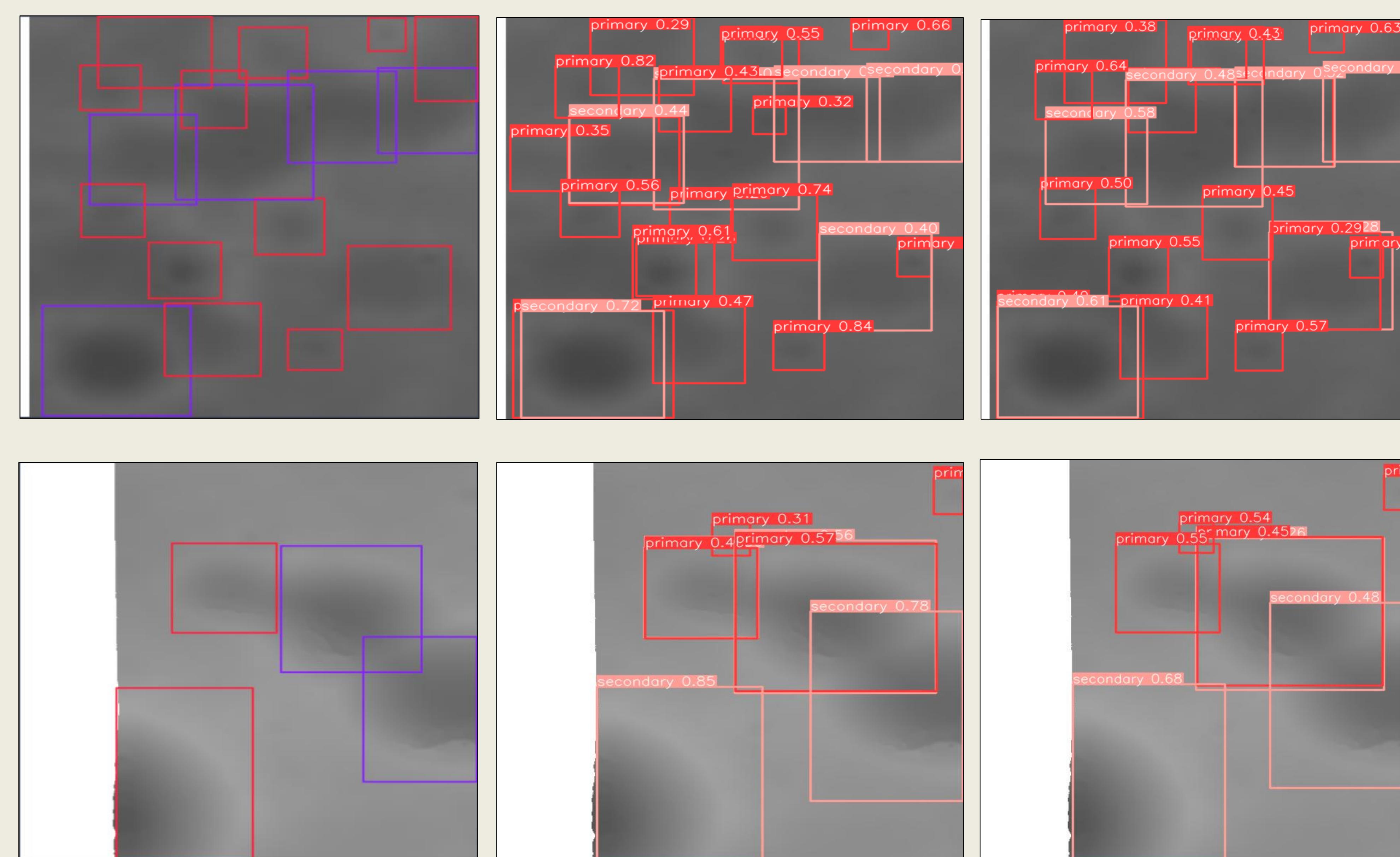


Figure 2. Left : Ground-truth image; middle : predictions from YOLOv8n; right : predictions from YOLOv8s

Table 1. Performance evaluation

	mAP50	cls_loss
YOLOv8n	0.6099	1.698
YOLOv8s	0.584	1.521

Table 1 shows the mean average precision and class loss for both the models. We plan on increasing the training data further to have better results. But even on such small dataset consisting of only 208 images, the method seems to be promising.

Furthermore, we plan on verifying the new detections by rule based approach, i.e., by extracting the morphological parameters and observing the spatial distribution encompassing the chain or cluster arrangements.

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