e-ISSN: 2250-0758 | p-ISSN: 2394-6962
Volume-11, Issue-2 (April 2021)
https://doi.org/10.31033/ijemr.11.2.26

Intelligent Lunar Landing Site Recommender

Anthony Thomas[1], Digina Derose[2], Sahaya Cyril[3] and Smita Dange[4]
[1]Student, Department of Computer Engineering, Fr. Conceicao Rodrigues Institute of Technology, Vashi, Navi Mumbai, INDIA
[2]Student, Department of Computer Engineering, Fr. Conceicao Rodrigues Institute of Technology, Vashi, Navi Mumbai, INDIA
[3]Student, Department of Computer Engineering, Fr. Conceicao Rodrigues Institute of Technology, Vashi, Navi Mumbai, INDIA
[4]Assistant Professor, Department of Computer Engineering, Fr. Conceicao Rodrigues Institute of Technology, Vashi, Navi Mumbai, INDIA

[1]Corresponding Author: anthonythomas40000@gmail.com

ABSTRACT

Space exploration is brewing to be one of the most sought after fields in today's world with each country pooling in resources and skilled minds to be one step ahead of the other. The core aspect of space exploration is exoplanet exploration, i.e., by sending unmanned rovers or manned spaceships to planets and celestial bodies within and beyond our solar system to determine habitable planets. Landscape inspection and traversal is the core feature of any planetary exploration mission. It is often a strenuous task to carry out a machine learning experiment on an extraterrestrial surface like the Moon. Consequent lunar explorations undertaken by various space agencies in the last four decades have helped to analyze the nature of the Lunar Terrain through satellite images. The motion of the rovers has traditionally been governed by the use of sensors that achieve obstacle avoidance. In this project we aim to detect craters on the lunar landscape which in turn will be used to determine soft landing sites on the lunar landscape for exploring the terrain, based on the classified lunar landscape images.

***Keywords*—** Machine Learning, Lunar Terrain, Craters, Soft Landing Sites

I. INTRODUCTION

Space exploration is the revelation and investigation of space structures through ceaselessly developing space innovation. While the study of space is carried out mainly by astronomers with telescopes and satellites, the physical exploration of space is conducted both by unmanned robotic probes and human spaceflight. Although the investigation of outer space is completed essentially by cosmologists with telescopes and satellites, the actual investigation of outer space is directed both by automated mechanical tests and human spaceflight.[1]

The Moon was the first extraterrestrial body to be the object of outer space exploration. It happens to be the first outer celestial body to be flown to and landed upon by a spacecraft and the only celestial body to be visited by humans.[2] There are abundant resources on the moon and hence makes it an ideal astronomical observation base. A lunar landing is the descent of a spacecraft on the surface of the Moon. This includes both crewed and robotic missions. The whole mission includes three phases known as 'orbiting, landing and returning'. In the second phase of lunar exploration, a lander and a rover will be launched whose mission is to land and explore on the Moon. [3] In a soft landing mission, the lander must keep a certain altitude so as to avoid toppling or rolling or slipping. Landing safety analysis is a prerequisite to committing any planetary landing and exploring mission. After acquiring the original terrain of the landing zone by on-board sensors and LIDAR, estimation about whether this terrain is suitable for soft landing is needed.

This work, hence attempts at using the Convolutional Lunar Network for classifying images of the lunar surface on the basis of presence of craters to determine whether it is suitable for soft landing or not.

II. LITERATURE REVIEW

A. Lunar Crater Identification via Deep Learning

In this paper they have trained a deep learning architecture known as a convolutional neural network (CNN) to perform crater identification on Lunar digital elevation map (DEM) images, and transfer-learn the Moon-trained CNN to identify craters on Mercury.[4] They have shown that their Moon-trained CNN can accurately detect craters on the substantially different DEM images of Mercury. This means that the CNN is not limited by the features that it has learned during its training phase and can accurately identify craters of any extraterrestrial landscape..

B. CraterIDNet: An End to End CNN for Crater Detection and Identification

Ali Hao Wang et al. offer a novel approach of using DEM end to end Conventional Neural Network for detection and identification, which takes remotely sensed planetary images of any size as the input and presents the apparent diameter, crater positions and indices of identified craters as the output by using two pipelines- one for detection of crater to determine if a crater is present in the picture and one for identification of crater to match the detected craters with respect to surface

This Work is under Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

e-ISSN: 2250-0758 | p-ISSN: 2394-6962
Volume-11, Issue-2 (April 2021)
www.ijemr.net
https://doi.org/10.31033/ijemr.11.2.26

landmarks in a known record. However, this research doesn't offer an insight on the classification of lunar surface between crater and non-crater.

C. Lunar Crater Detection based on Grid Partition using Deep Learning

This publication by the researchers Hashimoto and Mori at JAXA put forth a method of classifying the craters obtained by the LRO-NAC by using grid partitions.[6] However, this research doesn't offer a method to mathematically interpret misclassifications and neither doesn't it delve upon landing site detection.

D. Craters Detection on Lunar Surface

This paper focuses on identification of craters on the lunar surface using an algorithm proposed by the author.[7] The author has put forth a simple algorithm to identify craters on the lunar surface and determine a probable landing site by using two parameters namely distance and angle measurement.

III. PROPOSED SYSTEM

A. Problem Statement

With the development of technology such as reusable launch rockets and better planetary images, space exploration is going to be on the rise in the next decade. Thus there is no doubt that there will be several space missions each year conducted by different countries. The mission objective depends on whether it is an orbiting mission or an actual landing and analysis mission. Only the latter part would provide a clear aspect of the extra-terrestrial body. So the main challenge is to land the probe or rover on it and only then the analysis phase can be started. So before landing, it is obligatory to take thousands of high-resolution images of its surface. And then using mathematical computations for illumination, shadows, slopes and craters a landing site can be determined.

Using Convolutional Neural Network to leverage detection of craters on the surface (considering craters primarily as we assume that most of the terrestrial rocky planets in space have craters as the primary landscape feature and it is the most visible and detectable characteristic of a high-resolution image of the planetary surface). Once detected different Machine Learning techniques are used to determine and suggest suitable landing sites on the planetary surface.

B. Scope

The project work presented in this paper and the developed model can be used to classify craters based on the data acquired from LRO-NAC datasets and thereby determine soft landing sites that will benefit space organizations around the world in planning their space missions. The model developed could be used by space agencies in future explorations. This implementation could also be added to Moon Trek by NASA which is an interactive navigation tool that allows users to not only view the moon but do a plethora of amazing activities such as view the lunar layers, see all the past lunar mission outposts and even experience a virtual lunar trek.

C. Proposed Solution

A convolutional neural network is first built, developed and trained that first classifies whether there is a crater or not in a lunar landscape image. Considering the resolution, each image will be cropped and each cropped part will be fed into the CNN for labelling crater or not. A threshold will be set to determine which images that are produced as output by CNN will be considered for landing site determination. Say, a 75% or 80% non-crater image will be used for determining suitable landing sites. Those images that are favorable for landing will be labelled as Yes and the rest as No. The final output as favourable landing site or not will be displayed to the user.

IV. DESIGN OF THE SYSTEM

A. System Architecture

a. Block diagram: Fig. 1 shows the different parts of the system as blocks which are connected by lines that show the relationship between the blocks. It is divided into two phases.

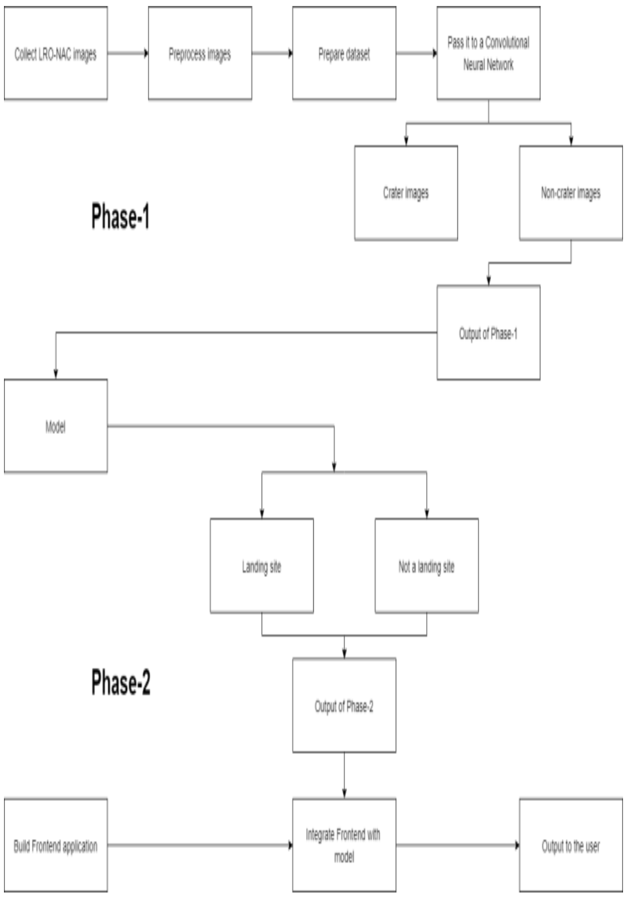

Figure 1: Block Diagram

b. Activity diagram: Fig. 2 shows the various functions of the system.

This Work is under Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

e-ISSN: 2250-0758 | p-ISSN: 2394-6962
Volume-11, Issue-2 (April 2021)
https://doi.org/10.31033/ijemr.11.2.26

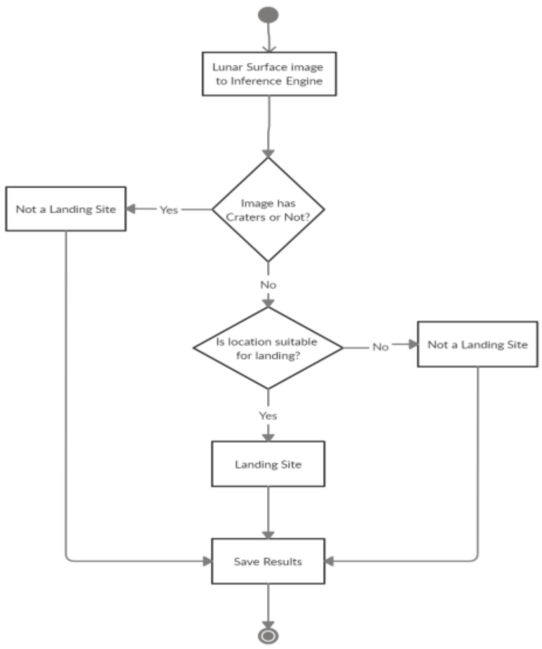

Figure 2: Activity Diagram

c. Use case diagram: Figure 3 shows how an actor interacts with the system to achieve a goal using a list of actions.

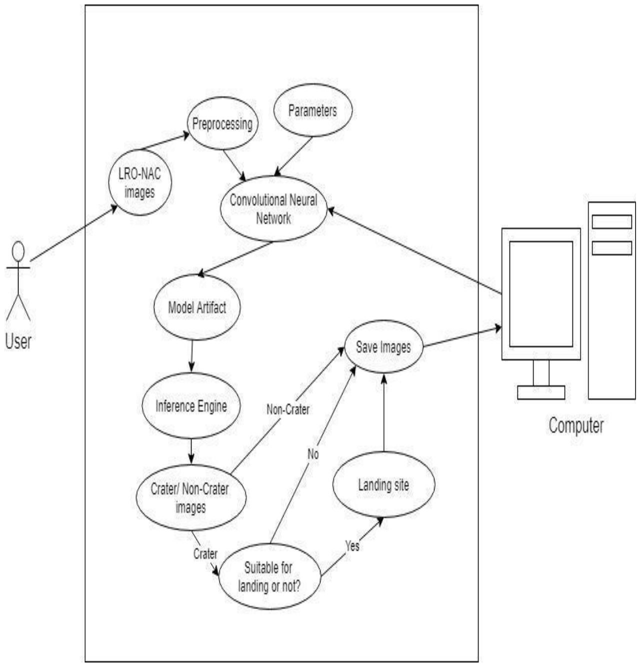

Figure 3: Use Case Diagram

V. RESULTS AND DISCUSSION

A. Approach

A Convolutional neural network was implemented for the project with the aim of determining whether there are craters or not and if not then whether it could serve as a good landing site or not. Following were the steps involved:

Phase 1:

a) Data collection

Going forward with the approach of classification of extraterrestrial landscapes and determination of probable landing sites there was no doubt that a large image dataset would be required. With the help of our external guide Mr. Sanket Korgaonkar we were able to contact the folks at NASA and JPL. They provided us images of the lunar landscape.

b) Dataset preparation

10 images were shared which were extremely large to be used by a Convolutional neural network. It required initial processing to convert it to be easily used by the model. Each shared image had a separate dedicated CSV file. The CSV file consisted of crater areas with many parameters such as x and y coordinates, height, width, etc. Using these parameters the single large image was cropped into many smaller images. These smaller images were then labelled to be fed to the convolutional neural network.

c) Dataset labelling

As explained above, each image had its own CSV file. All the crater area parameters were stored in that CSV file. Based on these parameters the large image was cropped resulting in several smaller images which were labelled as craters. The remaining areas that were left out were cropped into quadrilateral shapes based on their neighbouring areas and were labelled as non-craters. After the process of labelling, the next step was to split this dataset.

d) Dataset splitting

The above collection of crater and non crater images would be used to train the model. But before feeding it to the model the dataset was split into 2 parts: training dataset and testing dataset. Table 1 shows the distribution of the dataset split:

Table 1: Dataset Information

Parameter	No. of images
Total images	1840
Training dataset images	1400
Testing dataset images	440
No. of classes	2

e) Model creation

A Convolutional neural network was created for taking images as input and determining whether there are craters or not in the image. It is a sequential model with 3 conv2D layers, 3 max pooling layers, 2 dense layers and 1 flatten layer. The output for the model was Crater or Not Crater depending on the type of image fed to it. This output was used as input in Phase 2. Figure 4 depicts the model.

This Work is under Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

e-ISSN: 2250-0758 | p-ISSN: 2394-6962
Volume-11, Issue-2 (April 2021)
https://doi.org/10.31033/ijemr.11.2.26

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 98, 98, 32)        896
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 49, 49, 32)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 47, 47, 64)        18496
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 23, 23, 64)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 21, 21, 64)        36928
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 10, 10, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 6400)              0
_________________________________________________________________
dense_2 (Dense)              (None, 512)               3277312
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 513
=================================================================
Total params: 3,334,145
Trainable params: 3,334,145
Non-trainable params: 0
```

Figure 4: Model Summary

Phase 2:

Based on the above output the model was tweaked a bit based on the output images. Since output images detected as craters won't be required, only the output images detected as Not Crater in the phase 2 were used. The scope of the project was narrowed down on the basis of only one landing site parameter, i.e, presence or absence of craters that were taken into consideration for the Apollo-11 mission.

a) Frontend

The aim was to create a simple user interface for the end user who would be using the application. The users of this application would mostly comprise space scientists and space enthusiasts. But not just limiting to these sectors of people efforts were taken to ensure that even a normal person could use this application out of simple curiosity. Flask was used for creating the application which houses the model at the backend and HTML, CSS and JavaScript pages housed the frontend of the application. The frontend template takes user input in the form of a lunar landscape image which it passes to the model at the backend. The model processes it and passes the predicted result to the frontend page to display it to the user.

b) Outcome

In order to gain insight as to how the model has worked following metrics and evaluation methods were used.

A) Confusion Matrix

A confusion matrix is a technique for summarizing the performance of a classification algorithm.[8]

```
Confusion Matrix
[[248   6]
 [ 17 148]]
```

Figure 5: Confusion Matrix

Figure 5 depicts the confusion matrix of the developed model.

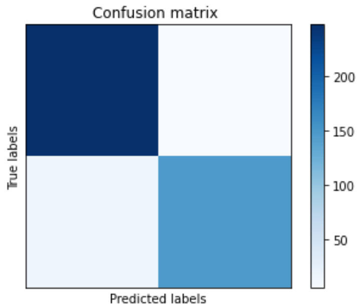

Figure 6: Plot of Confusion Matrix

Figure 6 showcases the plot of the model's confusion matrix. The following list of terms are now used that are often computed from a confusion matrix.

B) Evaluation Methods

Following evaluation methods were used based on the confusion matrix to gauge the performance of the model.

Accuracy

It is the percent of predictions that the model was able to make correctly.

$$\frac{TP + TN}{TP + TN + FP + FN}$$

Precision

It tells us what proportion of positive identifications was actually correct.

$$\frac{TP}{TP + FP}$$

Recall

It tells us what percent of actual positive test cases were recognized accurately.

$$\frac{TP}{TP + FN}$$

F1 Score

It tells us the accuracy of a model on a dataset.

$$\frac{2 * Precision * Recall}{Precision + Recall}$$

From Figure 5 we have the following values:
TP = 248, TN = 148, FP = 6, FN = 17

Table 2: Computation of Evaluation Methods

Evaluation Method	Computed Value
Accuracy	95.11%
Precision	97.64%
Recall	93.58%
F1 Score	95.57%

This Work is under Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

e-ISSN: 2250-0758 | p-ISSN: 2394-6962
Volume-11, Issue-2 (April 2021)
https://doi.org/10.31033/ijemr.11.2.26

Table 2 shows the computed values of the evaluation methods. Figures 7 and 8 depict the accuracy and loss of our model respectively. Both plots are plotted against a number of epochs. The blue line depicts training accuracy and the orange line depicts testing accuracy in the model accuracy plot. Similarly, in the model loss plot, blue line indicates training loss and orange line indicates testing loss.

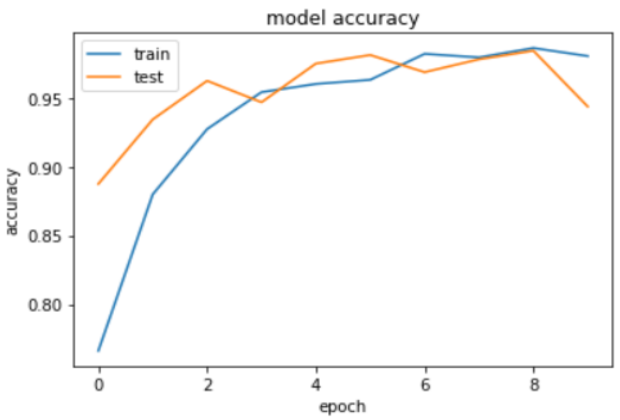

Figure 7: Plot of Model Accuracy

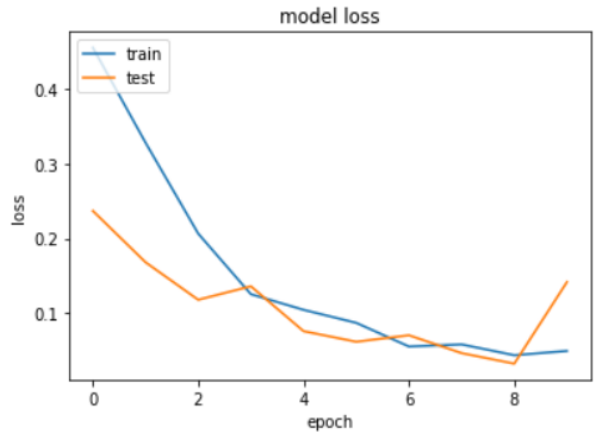

Figure 8: Plot of Model Loss

VI. CONCLUSION AND FUTURE SCOPE

Intelligent Lunar Landing Site Recommender is an ideal landing site recommender system developed such that it can be used to provide the user with probable landing sites on the lunar surface. The system initially takes images of the lunar surface as input and provides output to the user as to whether it could be a good landing site or not. The system makes use of Convolutional Neural Network which works as a classifier of craters and non-craters. The data for the model of the system was obtained by NASA. It consists of LRO-NAC images of the lunar surface. This system is developed mostly for space scientists and space enthusiasts all over the world. It can also be used by a normal user. The system has been designed in a simple way that the user is not burdened with any navigational discrepancies and can use the application with ease.

ACKNOWLEDGMENT

We would like to take this opportunity to express our heartfelt thanks to those who have been instrumental in the successful completion of this project. We would like to show our appreciation to our internal guide Ms. Smita Dange and our external guide Mr. Sanket Korgaonkar for their continuous support and help throughout the project. We would also like to extend our appreciation to our project supervisor Mrs. Rakhi Kalantri for providing us with timely inputs about documentation and project timeline. A big token of thanks to our HOD, Dr. Lata Ragha for the concrete guidance given to our team. Last but not least we would like to express our gratitude towards our principal, Dr. S. M. Khot, and our college, Fr. C. Rodrigues Institute of Technology, Vashi, for giving us the platform and the environment to learn and grow.

REFERENCES

[1] https://planetary-science.org/planetary-science-3/exploration-2/an-introduction-to-space-exploration/.
[2] https://en.wikipedia.org/wiki/Space_exploration/.
[3] Zhang, S., Yan, Z., & Wu, F. (2013). A lunar landing safety estimation methodology using lidar acquired DEM. In: *IEEE International Conference on Imaging Systems and Techniques (IST)*.
[4] Ari Silburta, Mohamad Ali-Diba, Chenchong Zhub, Alan Jackson, Diana Valencia, Yevgeni Kissinb, Daniel Tamayoa, & Kristen Menoua (2018). *Lunar crater identification via deep learning*. Available at: https://arxiv.org/abs/1803.02192.
[5] Hao Wang, Jie Jiang, & Guangjun Zhang. (2018). CraterIDNet: An end to end CNN for crater detection and identification in planetary images. *Remote Sens., 10*, 1067.
[6] Shintaro Hashimoto & Kenji Mori. (2019). *Lunar crater detection based on grid partition using deep learning*. Available at: https://ieeexplore.ieee.org/document/9111474.
[7] Nur Diyana Kamarudin, Siti Noormiza Makhtar, & Hizrin Dayana M.Hidzir (2011). *Craters detection on lunar*. Available at: https://ieeexplore.ieee.org/document/6015881.
[8] https://machinelearningmastery.com/confusion-matrix-machine-learning/.

This Work is under Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.