Increase the Exploitation of Mars Satellite Images Via Deep Learning Techniques

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***Abstract*—Mars is the fourth planet from the sun and the second smallest planet in the solar system after Mercury. Like Earth, Mars has a range of surface features such as valleys, deserts, and polar ice caps. Scientists around the globe have developed a specific interest in the terrain and climate of Mars because it is believed to have the potential to host life. To assist scientists to discover past or present life on Mars, we developed machine learning models (based on deep learning) to analyze the satellite images received from the Red Planet. The models automatically eliminated satellite images that were of a low quality and subsequently classified the high-quality images based on climate/environmental conditions. The models were tested on sample datasets and demonstrated the ability to achieve considerable accuracy. We also integrated additional functionality to convert two-dimensional (2D) satellite images into an informative (3D) format for better analysis and exploration. Furthermore, the solution was integrated into a mobile application that can be used by scientists and members of the public who are interested in space science**.

Keywords- Mars, space science, deep learning, NIMA, satellite images, 3D images.

I. INTRODUCTION

In recent times, the Red Planet has been rigorously explored during several orbital missions that aim to generate meaningful insights into the climate/environmental conditions on Mars as a means of evaluating its possible habitability and the way in which the climate/environmental changes—which result from a variety of factors such as dust storms, ice caps, volcanos, and water vapor—on this planet compare with those observed on Earth.

Satellite images that offer a higher meter- and decimeter-level resolution are commonly employed to study geological features and climate/environmental changes, and having access to a significant number of Mars orbital images enables researchers to study these changes. The majority of satellite images that are available can be accessed by researchers and members of the public thanks to the Planetary Data System (PDS), National Aeronautics and Space Administration (NASA) [1]. These images can be used to detect changes on Mars such as the formation of gullies [2], the emergence of new impact craters [2], dark slope streaks [3], and dust devil tracks [4].

Historically, feature-based algorithms [5] have been employed to study satellite images from Mars as a means of detecting scene breaks. Other satellite image analysis methods have also used to automatically detect features on the surface of Mars such as craters fields [6] and dune fields [7]. Kaichang Di et al. [8] employed a feature-based method and associated computational framework to detect changes. Several features were extracted to identify interesting regions by relying on the detection of edges linking and pixel greyscale statistics. Eventually, the regions in which changes could be observed were detected according to multiple difference information. However, the surface of Mars is very different from that of Earth; specifically, it exhibits fewer features and lacks texture in most areas. As such, changes on the surface of Mars are usually of high visual salience and can be distinguished from the monotonous background [8]. Therefore, it is entirely feasible that advanced machine learning methods are capable of classifying images into climate/environmental conditions such as Aeolian, Dry, Glacial, and Volcanic.

Machine learning (ML) techniques are becoming increasingly important and are widely employed in many aspects of daily life including automatic image/video search, autonomous driving, and recommendations on e-commerce web pages. ML techniques depend on careful engineering and significant domain knowledge to construct intelligent systems. Recently, deep learning techniques have [9] revolutionized many areas of computer science, including computer vision, leading to the development of dramatic performance improvements that can address a variety of traditional problems. Within deep learning, convolutional neural networks (CNN) [10] have attracted significant attention in recent times and have been widely adopted by the computer vision community. These CNNs take a fixed sized RGB image as input to a series of convolution, local normalization and pooling operations (known as layers). Generally, the final layers in the CNNs, which are employed for feature extraction and classification, are fully connected. CNNs typically require a large-scale corpus due to the optimization of a large number of parameters (typically in millions), thereby making it difficult to generalize these networks well with limited data. To this end, the recent rapid and significant development of pre-trained word embedding and CNNs have been successfully employed in different Natural Language Processing (NLP) tasks. For example, Razavian et al. [11], explored the applicability of CNN to infer useful features rather than hand-coding them. By using CNNs, researchers were able to achieve a better performance when detecting two Mars surface features of interest (volcanic rootless cones and transverse Aeolian ridges) in orbital images [12]. However, the accuracy of the analysis would have been further improved if CNNs had first been applied to detect high-quality images.

In the past, numerous matrices for assessing the quality of images have been developed. An image goes through several stages before it is presented to the end-user. These include storage, processing, compression, and transmission, and can be a source of malformation [13]. In terms of results, the quality of an image is subjected to reduction and distortions. These might include noise, blurring, ringing, and compression. Two evaluation techniques are typically employed to assess the quality of an image: subjective evaluation and objective evaluation [13]. Subjective evaluation is based on human observers as they are the end-users of most applications. However, this evaluation is impractical for real-time applications. Therefore, considerable efforts have been invested in improving objective evaluation. Objective measures are divided into three categories: full reference quality metrics (which compare the original image to a reference image that lacks distortions), reduced reference quality metrics (where the reference image is available in a set of extracted features only), and no-reference quality metrics (where the reference image is not available and quality is computed by comparing the statistical features of the original image against a trained model) [13].

One of the earlier methods of image quality assessment (IQA) was that of the human visual system (HVS) [14], which was later improved by Wang et al. [15] who proposed a structural similarity (SSIM) IQA corresponding to sensitivity to structural information in HVS. Another commonly used metric is the peak-signal-to-noise ratio (PSNR) [16]. Additional methods that have been employed in emerging, practical real-world applications are NR-IQAs [17], Naturalness Image Quality Evaluator (NIQE) [18] and the Blind/Referenceless Image Spatial QUality Evaluator (BRISQUE) [19].

Machine learning has recently shown promising results in predicting image quality. For example, CNN-based methods have been found to exhibit a significant performance improvement in comparison to earlier methods based on hand-crafted features [20]. Although Kang et al. [21] used only one convolutional layer and two fully-connected layers in conjunction with deep CNNs to extract high-level features, they managed to achieve state-of-the-art blind quality assessment performance. This method was further improved by Bosse et al. [22] who used 12 layers as opposed to the three employed by Kang et al. Recently, Bianco et al. in [23] proposed a deep quality predictor based on AlexNet [24]. Multiple CNN features were extracted from image crops of size 227×227 and then regressed to the human scores. To the best of our knowledge, these successful methods have not yet been used to evaluate satellite images.

In this paper, we expanded upon the utilization of CNN to automatically eliminate images that are of a low quality and then classify high-quality satellite images based on climate and environmental conditions such as Aeolian (modification of the Martian surface, as caused by atmospheric dust storms, dust devils, and perhaps even tornados), dry, glacial (patches of flowing ice that cover large, but restricted, areas of the modern Martian surface), and volcanic (important for the geologic evolution of Mars and covers large portions of the Martian surface) features. Once the novel image was classified, we further converted it into a 3D format for better exploration.

II. METHOD

Our method has three main steps, automatic validation of the satellite images, the detection of the environmental conditions, and the automatic conversions of 2D images into a 3D format. Figure 1 presents an overview of the proposed framework.

A. Automatic validation of the quality of the satellite images:

The development of technologies that can automatically verify the quality of satellite images is becoming a crucial task within efforts to explore the composition, structure, and history of Mars as a planet and, thereby, generate data that will assist researchers to better understand its surface and interior. To validate the quality of the satellite images, we propose the use of a contemporary model known as NIMA: Neural Image Assessment [25]. Unlike the existing models, which tend to predict the mean opinion score provided by datasets, such as aesthetic visual analysis (AVA) [26] and Tampere image database (TID2013) [27], NIMA (a deep convolutional neural network) predicts the distribution rating of human opinion scores using a convolutional neural network [28, 10]. NIMA is trained to identify technically or aesthetically attractive images that would appeal to a user. It is capable of generalizing objects based on their categories. It relies on the success of proven, state-of-the-art deep object recognition networks to predict both the technical and aesthetic qualities of the images. In this study, we considered a model that was trained on AVA. The AVA dataset contains more than 255,000 images that are rated based on aesthetic qualities from 1 to 10 (with 10 being the highest) by around 200 amateur photographers. We considered the MobileNet model with SoftMax activation as the activation function.

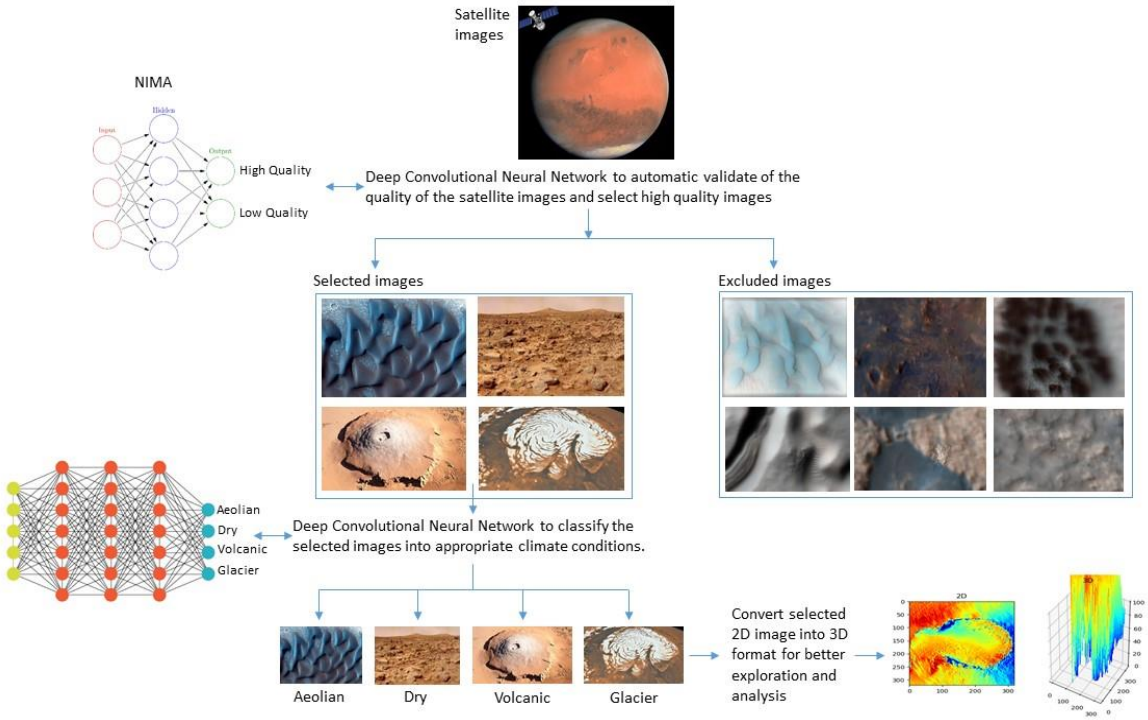

Figure 1. Overview of the proposed method.

B. *Detection of the environmental condition:*

We propose the use of CNNs to classify the high-quality satellite images identified in the previous step based on climate and environmental conditions. To achieve this, we adopted the traditional architecture, which consists of convolutional and max-pooling layers for the feature extractor and fully connected layers that perform non-linear transformations of the extracted features as the classifier. Once the model was developed, novel images were compared to the model and classified automatically.

C. *Converting of the 2D image into 3D format:*

In this step, we approximated the 3D projection of the images by using the Python Imaging Library (PIL) imaging package. PIL is a free library for the Python programming language that offers support for opening, manipulating, and saving many different image file formats.

D. *Development of a mobile app:*

One of the aims of this project is to raise awareness, knowledge, and interest in exploring Mars among the community and young researchers. Therefore, we implemented the proposed method in a mobile app. To enhance the efficiency of the app, we trained the CNN on a local server that was developed using Flask.

E. *Datasets:*

To evaluate the prediction performance of the model for satellite image quality, we retrieved 110 sample images from the NASA website "The Mars Today: Robotic Exploration portal" (https://www.nasa.gov/mission_pages/mars/images/-index.html), which is maintained by the National Aeronautics and Space Administration. The sample images are in jpg and Jpeg formats in a minimum width and height of 32.3 pixels. They contain 70 and 40 images of acceptable and poor quality respectively. Furthermore, another dataset that consisted of 50 Aeolian, 50 glacier, 50 dry, and 50 volcanic images was created to test the performance of CNN models as classifiers across these four climate conditions. The datasets are available from https://github.com/srikanthuaeu/MarsImagesAnalysis.

III. EXPERIMENTAL WORK AND RESULTS

In the first experimental work, we utilized NIMA to predict the distribution rating of human opinion scores using CNN. Here, we considered the model trained on AVA and VGG16 MobileNet model with SoftMax as the activation function. The dropout rate on the last layer before the fully connected layer was 0.75, the learning rate was 0.001, and the loss function was the Adam stochastic optimizer. From the 110 retrieved images, the model accurately predicted 98 images correctly (89.1%). The detailed results are summarized in Table I.

In the second experimental work, we split the 200 samples into two sets: 60% training set and 40% testing set. The images were rescaled to height, width = [150, 150]. The four layers CNN (Convolution 1, activation 1 [relu], MaxPooling 1, convolution 2, activation 2 [relu], MaxPooling 2, activation 3 [relu], dropout and fully connected layer, activation 4 [softmax]) were modeled with a drop-out rate of 0.5, learning rate of 0.0004, and RMSprop optimizer loss function. The model is able to distinguish between climate conditions with an average accuracy of around 91.5%. The detailed results of the prediction of the four climate conditions are summarized in Table II.

TABLE I. DETAILED RESULTS OF THE PREDICTION OF THE QUALITY OF THE SATELLITE IMAGES

Evaluation Measure	Formula	Accuracy Result
Precision (RR)	$\frac{TP}{TP+FP}$	0.857143
Recall (REC)	$\frac{TP}{TP+FN}$	0.967742
F	$2 * \frac{PR*REC}{PR+REC}$	0.909091
Overall Accuracy (ACC)	$\frac{TP+TN}{TP+TN+FP+FN}$	0.890909

TP= True Positive, TN = True Negative, FP= False Positive, FN = False Negative

TABLE II. DETAILED RESULTS OF THE PREDICTION OF THE FOUR CLIMATE CONDITIONS

Evaluation Measure	Aeolian	Dry	Glacier	Volcanic	Average
Precision (RR)	0.9	0.9167	0.8	0.7083	0.8351
Recall (REC)	0.75	0.8462	0.8	0.94	0.8313
F	0.8182	0.88	0.8	0.8095	0.8269
Overall Accuracy (ACC)	0.909	0.9318	0.909	0.909	0.9148

To explore the details of the image, an approximate 3D projection was obtained using the PIL Python-imaging package and the Matplotlib package. An example illustration is shown in Figure 2.

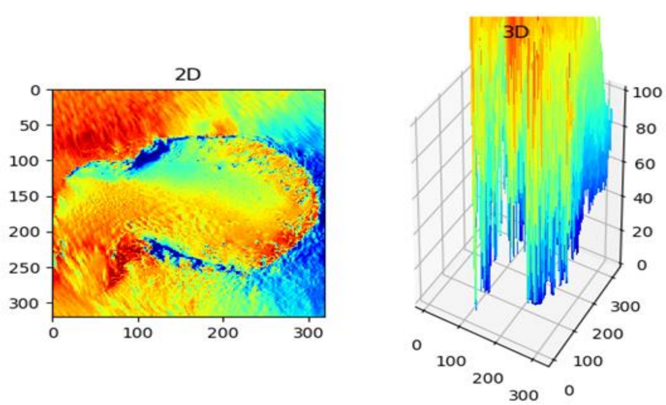

Figure 2. Figure 1: Example to illustrate the 2D to 3D conversion using the PIL Python-imaging package and the Matplotlib package.

Once the learning CNN models were developed, we used a Python-based server to host and access the proposed application structure, which distributes the tasks between the server and the client. The client needs an API to easily communicate with the server. We used Android Project in combination with Android Studio and implemented all the required functions to build the app and design the user interface. Postman (https://www.getpostman.com/) was used to independently test the APIs. A Python-based server was created using the Flask (http://flask.pocoo.org/) framework since the backend logic ran Keras: The Python Deep Learning library (https://keras.io/). In addition, Django (https://www.djangoproject.com) was utilized to build the web app. The app interface is shown in Figure 3.

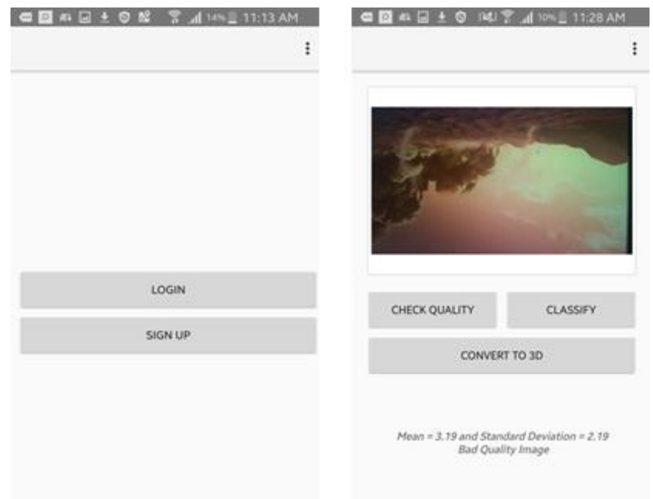

Figure 3. The user interface of the image exploration app

The final implementation of the proposed method is available at https://github.com/srikanthuaeu/MarsImages-Analysis. From here, the user can run the "python EvaluateQuality.py" program to start the prediction. He or she will then be prompted to select one of the following options:

- Option 1: Image aesthetic quality
- Option 2: Image classification
- Option 3: 2D to 3D approximate projection
- Option 4: Exit

Once option 1 is selected, the user needs to select a threshold value between 1 and 10 to determine the desired quality to be tolerated (5 is the default value). In this case, the program will select all the images that have an equal or higher quality than the threshold value before storing them in a dedicated folder. As soon as option one is completed, a second program will be run to classify the selected images into four categories: Aeolian, Dry, Glacier or Volcanic. The user can also select any of the predicted images to visualize them in 3D by selecting Option 3 from the main menu.

IV. CONCLUSION

In this paper, we introduced a flow of models and solutions by which scientists around the globe can investigate Mars in more depth to evaluate its possible habitability and the effects climate/environmental changes could have on Earth. This objective can be achieved by analyzing satellite images, which have long been the source of valid information that can be used to study geological features and climate/environmental changes. To this end, we first used NIMA (a deep convolutional neural network) to distinguish between high- and low-quality images. This step resulted in the automatic elimination of several low-quality images from the data and, subsequently, facilitated more efficient analysis of the available information. A second CNN model was developed to assist researchers to better predict the climate conditions that could be observed in the satellite images. Scientists can also visualize the images in 3D format for better exploration and analysis.

In the future, we are planning to extend the work to cover all potential climate conditions. We will also explore methods by which it is possible to compare images as a means of more effectively detecting changes in climate conditions. The accuracy of the predictive models can also be improved by training the model on more datasets spanning a wider variety of conditions. Comparing the performance of new models with the existing models will increase the credibility of our proposed solutions.

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