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Advance Dust Devil Detection with AI using Mars2020 MEDA instrument

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Introduction

Mars' dust cycle is a critical factor that drives the weather and climate of the planet. Airborne dust affects the energy balance that drives the atmospheric dynamic. Therefore, for studying the present-day and recent-past climate of Mars we need to observe and understand the different processes involved in the dust cycle. To this end, the Mars Environmental Dynamics Analyser (MEDA) station [1] includes a set of sensors capable of measuring the radiance fluxes, the wind direction and velocity, the pressure, and the humidity over the Martian surface. Combining these observations with radiative transfer (RT) simulations, airborne dust particles can be detected and characterized (optical depth, particle size, refractive index) along the day. The retrieval of these dust properties allows us to analyze dust storms or dust-lifting events, such as dust devils, on Mars [2][3].

Dust devils are thought to account for 50% of the total dust budget, and they represent a continuous source of lifted dust, active even outside the dust storms season. For these reasons, they have been proposed as the main mechanism able to sustain the ever-observed dust haze of the Martian atmosphere. Our radiative transfer simulations indicate that variations in the dust loading near the surface can be detected and characterized by MEDA radiance sensor RDS [4].

This study reanalyzes the dataset of dust devil detections obtained in [3] employing artificial intelligence techniques including anomaly detection based on autoencoders [5] and deep learning models [6] to analyze RDS and pressure sensor data. As we will show, preliminary results indicate that our AI models can successfully identify and characterize these phenomena with high accuracy. The final aim is to develop a powerful tool that can improve the database for the following sols of the mission, and subsequently extend its use for other atmospheric studies.

Dataset

The dataset used in this study includes data from 365 Martian days, which represents half a Martian year of observations and it was collected with a temporal resolution of one sample per second (for

12 hours in average observations per sol). This dataset, which has been labeled by hand, contains 424 detected Dust Devil events. The duration of these events varies considerably, ranging from just a few seconds to several minutes. The precise manual labeling is crucial for training reliable machine learning models that can effectively recognize and predict these events.

AI techniques

Deep learning is increasingly used to detect events in time-based signals, significantly enhancing accuracy and speed. Methods like CNN [7] and RNN [8] identify complex patterns effectively. These models learn from vast data, enabling real-time and predictive analytics.

Deep learning-based autoencoders are powerful tools for anomaly detection in temporal signals [5], offering a sophisticated method to capture complex patterns and identify outliers. Autoencoders, which are neural networks designed to reconstruct their input, learn to represent normal patterns during training. By minimizing the reconstruction error, these models learn to encode the regular, predictable aspects of temporal data. When an anomalous signal occurs, it typically results in a higher reconstruction error due to deviations from learned patterns.

The nature of the events and the low frequency of occurrence presents two main challenges for the Machine Learning algorithm:

• The database is highly unbalance. As it is said in Section Dataset, 424 events are detected over 365 Martian days. It means that less than 0.2% of the database corresponds to Dust Devil cases.

• Due to the spatial nature of the events, the Dust Devils manifests in different RDS sensors each time. This makes it difficult for the algorithm to generalize.

Results

For the experiments, the data is windowed and data augmentation techniques are used to try to correct the issue of class imbalance. The training set was selected randomly and intentionally balanced to ensure an equal number of samples per class. For testing the models, data from six randomly chosen suns are selected. The following results (Table 1) are obtained:

Name	Train Accuracy	Test Accuracy
DNN	75.0%	65.7%
CNN	82.5%	78.9%
LSTM	73.1%	67.0%

At the time of writing this document, there are no consistent results for autoencoder's approach.

Conclusions and Future Steps

This study demonstrates that data augmentation and advanced AI techniques can significantly improve the detection of dust devils on Mars. The use of deep learning, specifically convolutional neural networks (CNNs), has shown to outperform other models in accuracy both during training and testing phases.

Future work will focus on enhancing feature extraction, exploring new data augmentation techniques, and further developing autoencoders.

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