Article : Mars weather data analysis using machine learning techniques

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Purpose:

To analyze weather on mars for future aspects of Colonization on mars.

Data:

https://www.kaggle.com/imkrkannan/mars-weather-data

Part 1 of paper: Analysis of Pre-existing works

Table 1 Summary of the existing works

Author and year	Research	Methodology/ Parameters
Banfield et al. 2020	Study on Mars' atmosphere observed by Insight lander	Temperature profile, carbon dioxide condensation profile, atmospheric dust optical depth, pressure and wind variability, gravity waves
Giuranna et al. 2021	Studying Martian atmosphere using Planetary Fourier Spectrometer	Temperature profiles, dust and water depth, along with season, latitude, longitude, over six years
Martire et al. 2020	Study on numerical modelling and analysis of InSight's data	Air pressure, ground velocities, acoustic propagation pattern
Lorenz et al. 2020	Study on Martian atmosphere and environment	Dust, cloud, eclipses, transient pressure drops, sample light dips
Gramigna 2020	Analysis on the atmospheres of Venus and Mars	Calibration of radio frequencies for correcting errors related to plasma noise, thermal noise, spacecraft trajectory, spacecraft clock
Kereszturi et al. 2020	Observed the fluctuating temperature and humidity on Mars	Calcium chloride, calcium perchlorate, and magnesium perchlorate have the longest duration of deliquescence
Ordonez-Etxeberria et al. 2020	Study on local dust storm on Mars	Effects of the storm on Gale crater, based on the size and altitude of the storm
Holmes et al. 2020	Presented dataset incorporating a global record of martian weather data from 1999 to 2015	Mars Global Circulation Model (GCM) and spacecraft observations (dust, water, temperature, ozone)
Kruss et al. 2020	A study highlighting wind erosion on Mars	Wind tunnel experiments on parabolic flights (shear stress thresholds and erosion rates for varying pressure)
Heavens et al. 2020	Observed the gravity wave activity in the lower atmosphere of Mars	Mars Climate Sounder observations, consistent spatial distribution of wave activity
Korablev et al. 2021	Study on geophysical and biological activities on Mars' atmosphere	Detecting halogen gas ~ twenty times more than previously reported upper limits
Charalambous et al. 2021	A study on partitioning observed signals into seismic and environmental contributions	Comodulation and quantification of seismic motion, wind and pressure, determining environmental sensitivity
Szantai et al. 2021	A study on the Martian cloud climatology	Deriving the Reversed Ice Cloud Index (ICIR) and the Percentage of Cloudy Pixels (PCP)
Le Mouélic et al. 2020	Investigation on the surface of Mars	Virtual and augmented reality (3D terrain reconstruction)

Part 2 of paper : Methods:

- Convolution Neural Networks (CNN)
  For the time series forecasting, a one-dimensional convolution layer is added with some parameters such as rectified linear unit which is a linear function that helps to convert negative values to zero, maximum pooling layer that helps to calculate the maximum value in the selected feature map, 50 densenet and adaptive learning rate optimizer.

- Long Short Term Memory (LSTM)
  The model is trained through the usage of some parameters such as a sequential layer, dense layer 1, and adaptive learning rate optimizer.

- Gated Recurrent Unit (GRU)
  The model is trained through the usage of some parameters such as a sequential layer, GRU layer 3, dense layer 1, and adaptive learning rate optimizer (Medsker and Jain 1999).

- LSTM - stacked
  The model is trained through the usage of some parameters such as a sequential layer, LSTM layer 3, dense layer 1, and adaptive learning rate optimizer.

- CNN-LSTM
  In this paper CNN model consists of two convolutions layer and one pooling layer, and LSTM model consists of one neuron output layer.

Evaluation methods:

- MAE
- MSE
- RMSE
- R-squared coefficient

Results :

Machine learning models	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)	Coefficient of determination (R-squared)
CNN	0.0370	0.1923	0.1453	0.8292
GRU	0.0310	0.1287	0.1498	0.8566
LSTM	0.0294	0.1716	0.1257	0.8640
Stacked LSTM	0.0403	0.2008	0.1505	0.8138
CNN-LSTM	0.0401	0.2002	0.1608	0.8149

Conclusion : the LSTM model conveniently outperforms all the other models.