Mars weather data analysis using machine learning techniques

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RESEARCH ARTICLE

Mars weather data analysis using machine learning techniques

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Abstract
Curiosity of the human mind and the possibility of settlement in other planets to decrease the likelihood of human extinction have acted as a catalyst in the colonization mission of the planet Mars. Exploration, colonization and human missions to the planet are being supported by many public space agencies. Although there are several factors like toxic soil, low gravity, radiation exposures etc. that rule out the possibility of colonization, the presence of polar ice caps gives abundant hope to scientists towards making Mars habitable. Colonizing the planet also considers factors like atmosphere, soil, water content etc., and there seems to be an ongoing debate on how to make the planet habitable for mankind. In order to strengthen or weaken the claim there is a necessity to explore many other factors that may contribute to Mars' colonization in the future. Weather is one such factor worth exploring. In this paper we present some artificial intelligence techniques for analyzing Martian weather data. We rely on machine learning models like Convolution Neural Networks (CNN), Gated Recurrent Units (GRU), Long Short Term Memory (LSTM), stacked LSTM, and CNN-LSTM models to analyze the red planet's weather data. The models have been validated using statistical parameters such as MAE, MSE, RMSE and R-squared coefficient. Our analysis reports that the LSTM model outperforms all the baseline models with the R-squared value as 0.8640, and the MAE value as 0.1257.

Keywords Mars weather · Convolution Neural Networks (CNN) · Gated Recurrent Units (GRU) · Long Short Term Memory (LSTM) · CNN-LSTM

Introduction

Mankind has always been curious about space exploration and finding planets that may be habitable. Technological advancement in the fields of space exploration has made it possible for mankind to identify potential habitable planets and also deduce the planets that were once habitable. Planet Mars is our neighbor in the solar system and is believed to have supported life once (Tan and Sephton 2020). The polar ice caps and the deep river channels on the planet's surface are indicative of water that could have existed on the planet billions of years ago (Bibring et al. 2004). Over the last few decades, the red planet has been explored in as many ways as technology could support the Mars Exploration mission. Remote exploration by spacecraft, orbiters and rovers have contributed massive amounts of information. As human extinction has been predicted in the future by visionaries, futurists and scientists, the curious human mind searches for alternative habitable planets. While there are many other planets in the solar system, Mars is the only planet that is being thought of from the colonization perspective. This is due to several reasons. First, its relative similarity to that of Earth. The duration of a solar day on Mars is slightly more than twenty four hours. Likewise, the surface area of Earth and Mars are comparable. The surface area of Mars is nearly 28 % to that of Earth. The similar axial tilt of the two planets ensures similar seasons, although the length of the duration is a little longer owing to the length of Martian year which is almost twice as that of Earth. Finally, the presence of water ice on Mars makes it the perfect candidate for colonization. Colonization of Mars has been proposed and funded

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by various space agencies, and the first human mission to Mars is expected to happen shortly. In order to colonize the planet, there is a need to consider numerous features like the atmosphere, soil, water content etc. (Rogberg et al. 2010; Bak et al. 2017; Lauro et al. 2021). Atmospheric pressure on Mars being less than Armstrong limit would require habitable structures to be constructed using pressure vessels. The toxic atmosphere may be unfavorable for habitation, and the thin atmosphere may not filter the ultraviolet rays of the sun. The water on Mars is scarce, and the climate much colder as compared to Earth (Sharma et al. 2019). High amounts of chlorine and other components make the Martian soil toxic, which may not be favorable for vegetation. Artificial Mars habitats, and a water recovery system may be the solution to such challenges, but that would take years to prosper. However, owing to the fact that Lichen and cyanobacteria can survive in simulated Martian conditions, settlement could be considered in specific locations of Mars.

While there are many other characteristics that are yet to be explored, one interesting characteristic that could essentially contribute to survival of humans on the planet is the weather on the planet (Leovy 2001). Weather may define the state of the atmosphere, or the degree to which it is hot or cold, wet or dry, calm or stormy, clear or cloudy etc. It also emphasizes the daily temperature and precipitation status. Colonization of the planet would mean that humans stay on the planet for a prolonged time, and therefore there is a need to consider the environment on a daily basis. Moreover, colonization may also necessitate the need for vegetation, and weather may be a primary driver for that. Past research works have primarily focussed on comprehending the geology and habitability potential. Many questions have been raised on the radiation exposure, toxic soil, low gravity, lack of water etc. In order to strengthen or weaken the support for colonization, there is a need to debate, considering as many factors as possible. Weather is one such factor that has not been considered before. Moreover, the analysis performed previously purely relied on data that was submitted by spacecrafts, orbiters and rovers. The following are the main contributions of the article.

1. In this article, we analyze the Martian weather using one of the leading tools of technological advancement, i.e. Artificial Intelligence (Jha et al. 2019a, b; Rokbani et al. 2020; Priyadarshini 2018; Tuan et al. 2019).
2. We deploy several machine learning algorithms like Convolution Neural Networks (CNN), Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU) stacked LSTM and CNN-LSTM models to analyze the martian weather data.
3. The performance of the models has been validated using validation parameters like MAE, MSE, RMSE and R-squared coefficient.
4. This is the first article that presents an analysis of the Martian weather data using multiple machine learning techniques. This article is also the first of its kind to explore Mars weather data, and validate it using multiple statistical parameters.

The rest of the paper has been organized as follows. Section 2 incorporates the materials and methods in which we report the related works, machine learning algorithms and the proposed work. Likewise, Section 3 depicts the experimental analysis and results. Here we discuss the datasets, evaluation parameters and results, and comparative analysis. Finally, Section 4 presents the conclusion and future work.

Materials and methods

This section has been divided into three parts. In the first part we discuss the related works that have been done in the past with respect to analyzing weather, atmosphere and data obtained for the planet Mars, following which we state the artificial intelligence techniques considered for the study in the next section.

Related works

(Banfield et al. 2020) presented a study on Mars' atmosphere as observed by InSight lander in terms of unprecedented continuity, accuracy and sampling frequency. InSight reported a new atmospheric phenomenon in the higher frequency range, i.e. turbulence. The rover presents a temperature profile, carbon dioxide condensation profile, atmospheric dust optical depth, pressure and wind variability, and pressure fluctuations with respect to gravity waves and infrasound.

(Giuranna et al. 2021) evaluated the Martian atmosphere for twelve years using the Planetary Fourier Spectrometer to deduce sufficient information on Mars weather and climate. The study successfully retrieved atmospheric temperature profiles and surface temperatures, along with depths of dust and water ice. A new atmospheric dataset incorporating season, latitude, longitude, and local time over a span of six years was built. The seasonal extent, pattern and thickness of the North polar hoods (NPH) was observed. It was found that spatial and seasonal patterns repeat every Martian year.

(Martire et al. 2020) presented a study on numeric modelling and analysis of InSight's data. Air pressure and ground velocities have been taken into consideration for studying infrasound on Mars. Numeric simulations are used to characterize the acoustic propagation pattern, and atmosphere to ground coupling under acoustic waves. The data suggests that low frequency monotone events are trapped in infrasounds. The study is also capable of discriminating acoustic waves from meteorological perturbations.

(Lorenz et al. 2020) carried out a study to find scientific observations with respect to dust, clouds, and eclipses on Mars. The study was based on InSight solar arrays, which incorporate vortices due to transient pressure drops and dust. The observations are intermittent with a modest sample rate. Based on the observations, the Phobos eclipses can be associated with three single-sample light dips, which provides information about the Martian environment.

(Gramigna 2020) proposed calibration techniques to analyze the atmospheres of Venus and Mars. Frequency shifts on the radio signal are usually sent by the spacecraft to Earth-based ground stations. The study performs calibration of radio frequencies for correcting errors related to plasma noise, thermal noise, spacecraft trajectory, spacecraft clock etc., so that there is no bias in retrieving the atmospheric data. The results are analyzed and compared for both Venus and Mars, and while Venus's atmosphere seems to be thick and hostile, Mars' atmosphere is thin and friendly.

(Kereszturi et al. 2020) monitored the fluctuating temperature and humidity for identifying ideal periods of liquefaction on Earth and Mars. The atmospheric pressure on Mars is relatively less compared to Earth, however, temperature fluctuations can lead to high humidity values at night. Calcium chloride, calcium perchlorate, and magnesium perchlorate were observed to have the longest duration of deliquescence. Although Mars has low humidity, cold nights may lead to higher humidity, and night time slope winds may also have an impact on the humidity and temperature on the red planet.

(Ordonez-Etxeberria et al. 2020) analyzed the local dust storm on Mars with measurements and images. The study presents a detailed report on the effects of the storm on Gale crater, based on the size and altitude of the storm. The storm led to an increase in the amplitude of atmospheric pressure variation, and also elevated the temperature. There was a decrease in the UV signal, along with cooling of the surface around noon. The overall effects of the storm over the local meteorology lasted significantly longer.

(Holmes et al. 2020) proposed a dataset incorporating a global record of martian weather data from 1999 to 2015, based on Mars Global Circulation Model (GCM) and spacecraft observations. The atmospheric properties can be used to analyze the physical, dynamical and chemical behaviour of the atmosphere on Mars. The observations that form a part of this dataset are dust, water, temperature, and ozone from various instruments embedded in the orbiter spacecraft.

(Kruss et al. 2020) presented a study highlighting wind erosion on Mars and other terrestrial planets using wind tunnel experiments on parabolic flights. The experiments took into account Mars simulant sand, and led to shear stress thresholds and erosion rates for varying pressure. The shear stress threshold was seen to be much lesser than the Martian gravity reported earlier. The data was found to be consistent with previous research works. The study confirms that the data can be applied to exoplanets with low pressure atmospheres.

(Heavens et al. 2020) studied the gravity wave activity in the lower atmosphere of Mars based on the Mars Climate Sounder observations. The study successfully confirms that strong and moderately intermittent gravity wave activity can be observed all over the tropical volcanoes. It can also be observed throughout the middle to high latitudes for both hemispheres during fall and winter. The study also reported that gravity wave activity fluctuates during global dust storms, and strong variance is noted at night in parts of southern tropics during winter and fall. Finally, there is consistent spatial distribution of wave activity.

(Korablev et al. 2021) explored the geophysical and biological activities on Mars' atmosphere, by detecting halogen gas, which could have been released due to volcanic degassing or gas-solid reactions. The study confirmed widely distributed halogen gas, which is approximately twenty times more than previously reported upper limits. The 2018 global dust storm led to an increase in the halogen gas, which was later suppressed.

(Charalambous et al. 2021) presented a study on partitioning observed signals into seismic and environmental contributions owing to the noise in the Martian atmosphere. A temporal cross-frequency coupling across multiple bands due to wind fluctuations and atmospheric pressure leads to noise. The same has been investigated using comodulation and quantification of seismic motion, wind and pressure. Determining the environment sensitivity includes quantification of the wind and pressure injection for estimating the seismic content of possible marsquakes. Hence, the signal-to-noise ratio can be quantified with respect to environmental independence.

(Szantai et al. 2021) carried out a study on the Martian cloud climatology by deriving the Reversed Ice Cloud Index (ICIR) and the Percentage of Cloudy Pixels (PCP). The study provides an in depth analysis on the thickness of cloud and nebulosity of a regular grid. The PCP provides an accurate image of the cloud cover and also confirms the existence of cloud structures mapped with ICIR. The regions above Hellas Planitia, the Lunae Planum region and large volcanoes depict dense cloud structures. The diurnal cloud life cycle has been analyzed by considering data from specific topographic features and by averaging the data over larger regions.

(Le Mouélic et al. 2020) investigated the surface of Mars in yet another interesting way, i.e. by using virtual and augmented reality. By coupling the two with 3D terrain reconstruction, it is possible to simulate field trips to locations which would otherwise be impossible for humans to reach.

The study uses high resolution imaging along with spectral data from rovers and orbiters to create virtual environments for accurately representing the surface of the planet. The simulation also makes it possible for navigating on a global scale using orbital data, and exploring places where in situ data is available.

From the past research works, we can deduce that several research works aim at analyzing weather patterns of Mars, however, most of the work done is from the atmospheric perspective (Table 1). The studies are interesting and explore various folds of Mars weather in the form of weather data, dust storms, humidity, temperature, clouds, water, ice etc. While all these works use techniques like observations from data (and images), modelling, numerical analysis etc., little has been done from the perspective of Artificial Intelligence. In this paper, we analyze Martian weather data using certain Artificial Intelligence techniques or machine learning models, which we discuss in the next section.

Artificial intelligence techniques

The following Artificial Intelligence techniques have been used to analyze the Martian weather data:

1. Convolution Neural Networks (CNN)

A convolutional neural network (CNN) may be defined as a deep learning neural network that may be used for processing structured arrays of data. CNNs are extremely good at comprehending patterns in the input image (Albawi et al. 2017). The details may incorporate circles, gradients and other intricate features. CNNs may not even need any kind of preprocessing and be operated directly on raw images. The CNN architecture boasts of a multi-layered feed-forward neural network. This network comprises sequentially combined hidden layers on top of each other. Such a design ensures that CNN can effectively learn the hierarchical features. These hidden layers

Table 1 Summary of the existing works

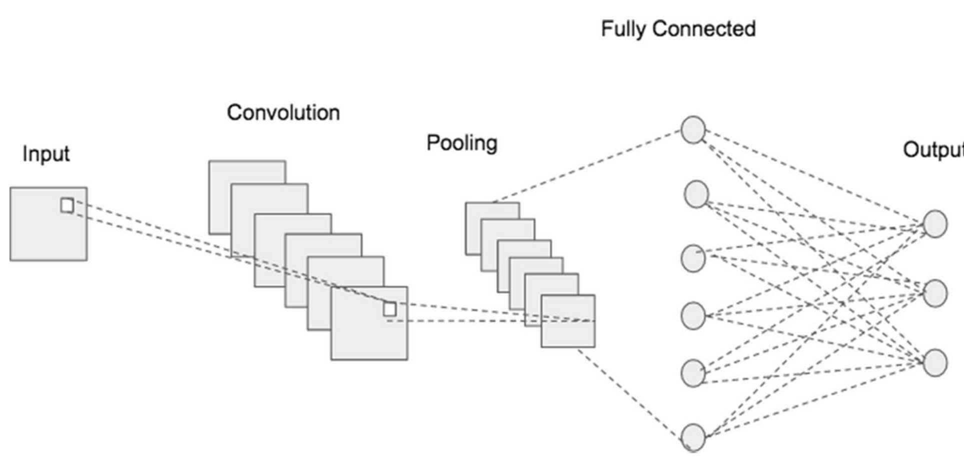
Author and year	Research	Methodology/ Parameters
Banfield et al. 2020	Study on Mars' atmosphere observed by Insight lander	Temperature profile, carbon dioxide condensation profile, atmospheric dust optical depth, pressure and wind variability, gravity waves
Giuranna et al. 2021	Studying Martian atmosphere 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)

are nothing but convolutional layers along with activation layers and pooling layers. Yann LeCun presented an early CNN LeNet-5 which describes the core design principles of CNN, and is capable of recognizing handwritten characters (LeCun 2015). The convolution layer (CONV) relies on filters for performing convolution operations after image scanning (dimensions). The primary hyperparameters are the filter size and stride (S). Feature map is known as the resulting output (O) or activation map. It incorporates all the features that have been deduced by the input layers and filters. The pooling layer is responsible for downsampling of the features. It is usually placed after a convolution layer. The pooling operations can either be max and average pooling. In this function, the maximum and average value of features is considered. Finally the fully connected layer (FC) is placed at the end of the network where the input is connected to all the neurons. The underlying idea is to connect the hidden layers to the output layer for optimized output. As the combination of these operations repeats, the first layer operates on simple features, while the second layer detects higher-level features. As the layers increase, the CNN becomes more robust and is able to detect more complex details (Priyadarshini and Puri 2021). This is due to the repeated layering of operations, such that each layer detects slightly higher-order features than its predecessor. A CNN relies on fewer parameters with respect to the fully connected feedforward neural network considering the same layer dimensions. 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. Figure 1 depicts the basic structure of CNNs.

2. Gated Recurrent Units (GRU)

A Gated Recurrent Unit (GRU), has architecture similar to RNN but relies on gating mechanisms for controlling and managing the flow of information Table 1. The information flows between cells in the neural network (Chung et al. 2015) and may be considered as an adaptation of LSTMs. GRUs are capable of adaptively capturing dependencies from large sequences of data such that there is no need to discard information from previous parts of the sequence. Gating units particularly address the vanishing/exploding gradient problem inl RNNs and are capable of regulating the information to be saved or rejected at every step. The functioning of GRUs is very similar to RNNs, because the sequential input data is considered by the GRU cell at every time step along with the hidden state or memory. This hidden state is again fed to the RNN cell along with the next input data in sequence. A relay-like mechanism is followed to produce the desired output. GRU can hold long term dependencies or memory stems from computations deduced from GRU cells for producing the hidden state. In case of LSTMs, there are two different states between the cells, i.e. the cell state and the hidden state for carrying the long and short term memory. But in the case of GRU, there is only one hidden state transferred between time steps. This state is capable of holding both long term and short term dependencies simultaneously, owing to the computations and gating mechanisms. GRU cells are equipped with the Update gate and the Reset gate, which are trained to selectively filter irrelevant information for storing useful ones (see in Fig. 2). The gates may be thought of as vectors incorporating values between 0 and 1, these values are multiplied with the input data or/and the hidden state. The value 0 refers to data in the input to hidden state being unimportant, hence is returned as 0. The value 1 refers to data being important and can be used. For the proposed study, the initial steps for the dataset are similar. 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).

Fig. 1 Structure of CNN



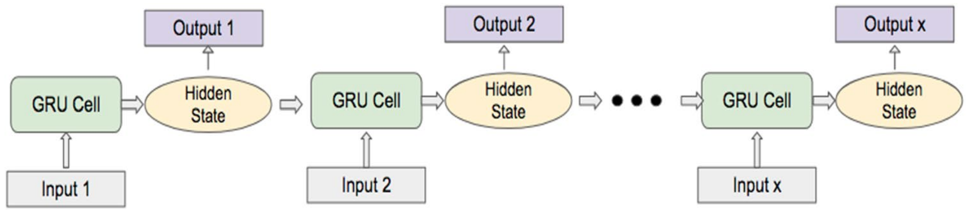


Fig. 2 Structure of GRU

3. Long Short Term Memory (LSTM)

LSTM stands for long short term memory, and these are a type of recurrent neural networks (Priyadarshini and Cotton 2021). The LSTM model or architecture extends the memory of RNNs. Usually, RNNs have 'short term memory' as they rely on persistent previous information that will be used in the current neural network (Hochreiter and Schmidhuber 1997). Thus in LSTMs, the previous information is used for carrying out the present task. LSTM is responsible for introducing long-term memory into RNNs. It is effective in mitigating the vanishing gradient problem, in which the neural network stops learning due to updates to the various weights within a given neural network becoming smaller and smaller (Jha et al. 2019). A series of gates are used to achieve these operations. The gates are incorporated into memory blocks and are connected using layers. There are different types of interacting layers, and they may be repetitive. Once the output of the previous state is obtained, the Forget gate is responsible for taking decisions regarding what must be eliminated from the previous state. It keeps only relevant stuff and is surrounded by a sigmoid function to accommodate the input between [0,1]. The input gate witnesses adding new stuff from the present input to the present cell state. The sigmoid layer is responsible for considering which values must be updated. A tan*h* layer creates a vector for new candidates which must be added to the present cell state. The output is given from the cell state based on the sigmoid function. The input is multiplied with tan*h* to accommodate the values between (-1,1). This is followed by multiplying it with the output of the sigmoid function. Thus, the outputs can be managed. LSTMs find their uses in many applications like handwriting recognition, Time series anomaly detection, Speech recognition, etc. (Priyadarshini and Cotton 2020; Dansana et al. 2020; Vo et al. 2020). For the proposed study, the initial steps for the dataset are similar. The model is trained through the usage of some parameters such as a sequential layer, dense layer 1, and adaptive learning rate optimizer.

Every unit in the LSTM model consists of the memory cell and three different gates such as input, output and skipped. Through this architecture, LSTM models are able to manage the flow of informatics knowledge by making decisions such that one is needed to "skip" and the other one "remember". Input gate x with second gate q*t, handles the new informatics knowledge that is stored in the memory cell qt at t−1 time and got output gate handles the informatics knowledge (Livieris et al. 2020) and can be used for the memory cell outcome.

$$x_t = \sigma\left(U_x i_t + W_x h_{t-1} + b_x\right) \tag{1}$$

$$g_t = \sigma\left(U_c i_t + W_c h_{t-1} + b_c\right) \tag{2}$$

$$q^*{}_t = \tanh\ \left(U_q i_t + W_c h_{t-1} + b_c\right) \tag{3}$$

$$q_t = c_t \ \Theta \ q_{t-1} + x_t \ \Theta \ q^*{}_t \tag{4}$$

$$go_t = \sigma\left(U_{go} i_t + W_{go} h_{t-1} + b_{go}\right) \tag{5}$$

where i_t is input, W and h are the network weight, b refers to bias terms vectors. σ and Θ are the sigmoid function and operator for multiplication respectively.

4. Stacked LSTM

A Stacked LSTM architecture comprises several LSTM layers. An LSTM layer above is responsible for providing a sequence output. It may not provide a single value output to the LSTM layer below. This may be also thought of as one output with respect to input time stem, and not one output time step for all input time steps. LSTM stacking is largely responsible for allowing greater model complexity. Feedforward networks witness stacking multiple layers for creating a hierarchical feature representation of the input data, so that it can be used for learning (Quek et al. 2019; Pritam et al. 2019). Similar architecture is there in LSTMs such that at every step there will be an LSTM along with the recurrent input. In the case that the input is a result of an LSTM layer (feedforward layer), the current LSTM may be capable of creating significant complex feature representation with respect to the current input. For the proposed study, the initial steps for the dataset are similar. 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.

5. CNN-LSTM

The CNN-LSTM architecture incorporates Convolutional Neural Network (CNN) layers which are responsible for feature extraction on input data, whereas the LSTM layers are responsible for supporting sequence prediction (Yang et al. 2020). This hybrid architecture is applied for problem solving in visual time series prediction and generating textual descriptions from sequences of images. The CNN layer consists of the convolutions and pooling layers which are used to compute the complex mathematical equations for developing extracted features from the input data and the LSTM layer exploits the features which are extracted via CNN. In this study, CNN model consists of two convolutions layer and one pooling layer, and LSTM model consists of one neuron output layer (see Fig. 3).

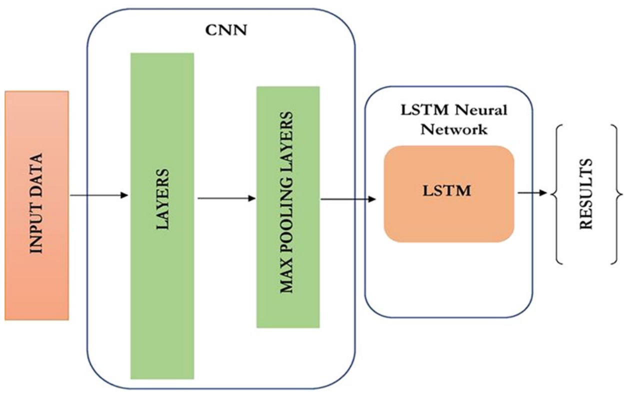


Fig. 3 Structure of CNN-LSTM

Proposed work

In this section, the overall methodology of the study is discussed as follows (see in Fig. 4).

a. *Dataset*: The first step is to collect Mars weather data from the kaggle repository (discussed in Section 3.1). The study uses libraries such as Numpy and Pandas for analyzing the data, and preparing it for the machine learning models. After successful initialization of libraries, the dataset is imported for further processing (https://www.kaggle.com/imkrkannan/mars-weather-data).
b. *Data Preprocessing*: There are a number of variables in the dataset such as id, terrestrial date, sol, ls, month,

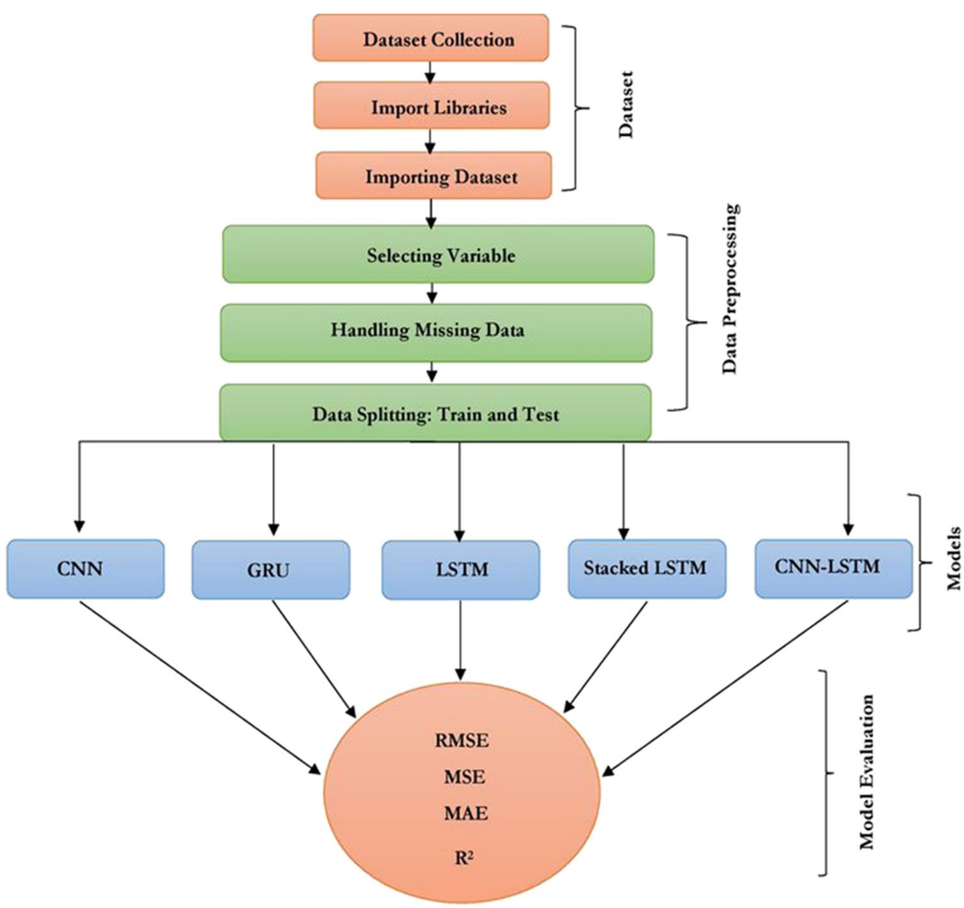


Fig. 4 Overall methodology of the work

minimum temperature, maximum temperature, pressure, wind speed, atmosphere capacity. For the data pre-processing, there is selection of variables that need to be used in the system for prediction. In this study, we consider terrestrial date and maximum temperature on Mars. Dataset contains "NaN" values which are fixed via the Pandas library and then splitted into the train and test dataset (50–50).

c. *Machine learning models*: The dataset has been split into 50% training set and 50% test sets. After splitting the dataset into train and test set, different machine learning models are applied such as CNN, GRU, LSTM, stacked LSTM and CNN-LSTM (discussed in Section 2.2). Every model is trained via 50 epoches to achieve high accuracy.

d. *Model Evaluation*: To evaluate the model performance, four different parameters have been used i.e. Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Coefficient of determination (R-squared). The data has been used to plot the predicted data with respect to the actual data (discussed in Sections 3.2 and 3.3).

Experimental analysis and results

In this section, we discuss the dataset and the evaluation parameters. We present the results based on the evaluation parameters. Finally, a comparative analysis has been presented to support our claim.

Dataset

The dataset has been taken from Kaggle 'Mars weather data' (https://www.kaggle.com/imkrkannan/mars-weather-data) (Kannan 2020). This dataset incorporates the weather conditions on Mars between Sol 1 and Sol 1985, which are August 7, 2012 February 27, 2018 on Earth respectively. The Rover Environmental Monitoring Station (REMS) on-board the Curiosity Rover was responsible for transmitting the data, which was publicly made available by NASA's Mars Science Laboratory and the Centro de Astrobiología (CSIC-INTA) respectively. The values are read by Rover Environmental Monitoring Station (REMS) on board the Mars Science Laboratory (MSL) rover on Mars, and presents some environmental magnitudes at REMS location. MSL rover has an influence over the magnitudes with respect to position, temperature, orientation, shade, dust deposition etc. The measurements have not been taken continuously, rather different measurements have been taken at different times on different days. This may have an impact over the variation of values. Since there may be limitations with respect to instrument maintenance, calibration, and instrument degradation, many of the magnitudes in this file could be inaccessible.

Evaluation parameters

The following evaluation parameters have been considered for the study.

a. Mean Absolute Error (MAE): MAE (Mean absolute error) is used to define the difference between the actual (y) and predicted ($\hat{y}$) values obtained by averaging the absolute difference over the data set. 1/N represents the total number of data points. MAE may be thought of as the summation of the absolute value of the differences between all the expected values and predicted values, considering the total number of predictions (Priyadarshini et al. 2021).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}| \tag{6}$$

b. Mean Squared Error (MSE): MSE (Mean Squared Error) is used to identify differences between the actual and predicted values obtained by squaring the average difference over the data set. It is an estimate of the average squared difference between the predicted values and the original value (Patro et al. 2020).

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y})^2 \tag{7}$$

iii. Root Mean Squared Error (RMSE): RMSE (Root Mean Squared Error) is the standard way of measuring the error of a model with respect to prediction of quantitative data. It is calculated by finding the difference between estimated values and the original values (Puri et al. 2019).

$$\mathrm{RMSE} = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y})^2} \tag{8}$$

iv. Coefficient of determination (R-squared): R-squared (Coefficient of determination) is responsible for quantifying the predictive accuracy of a statistical model. It depicts the proportion of variance in the outcome variable with respect to the predictions. It is used to comprehend how well the values fit compared to the actual values. It ranges from 0 to 1, such that the higher the value is, the better the model is (Puri et al. 2019).

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \quad (9)$$

Results

The following table depicts the performance evaluation of the models considered for the study. The baseline algorithms considered for the study are CNN, GRU, LSTM, stacked LSTM and CNN-LSTM. The statistical parameters used for the evaluation are MAE, MSE, RMSE and R⁻squared coefficient.

Table 2 depicts the performance evaluation of all the machine learning models considered for the study. As we have discussed before, the performance evaluation metrics are MSE, RMSE, MAE and R-squared. We observe that the MSE values for CNN, GRU, LSTM, stacked LSTM and CNN-LSTM are 0.0370, 0.0310, 0.0294, 0.0403 and 0.0401 respectively. The RMSE values are 0.1923, 0.1287, 0.1716, 0.2008 and 0.2002 respectively. The MAE values are 0.1453, 0.1498, 0.1257, 0.1505 and 0.1608. And finally, the R-squared coefficient values are 0.8292, 0.8566, 0.8640, 0.8138, and 0.8149 respectively. Based on the values, it is evident that lower the values better the model. Considering MSE, LSTM performs better compared to other models at a value 0.0294, and stacked LSTM performs poorly with an MSE 0.0403. In the case of RMSE which is an even more sensitive parameter, we find that GRU performs the best with value 0.1287 while stacked LSTM performs poorly with the value of RMSE 0.2008. The MAE values depict that LSTM performs best with the MAE value 0.1257 while CNN-LSTM performs poorly with the value 0.1608. Finally, based on the R-squared coefficient value, we observe that LSTM is the most efficient model with the R-squared value 0.8640 and stacked LSTM is the weakest model with value 0.8138. We depict the results in the following figures.

Figure 5 determines the performance evaluation of the machine learning models based on MSE. As we can see LSTM has the lowest value while stacked LSTM has the highest value.

Figure 6 determines the performance evaluation of the machine learning models based on RMSE. As we can see GRU has the lowest value while stacked LSTM has the highest value.

Table 2 Performance evaluation of the models

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

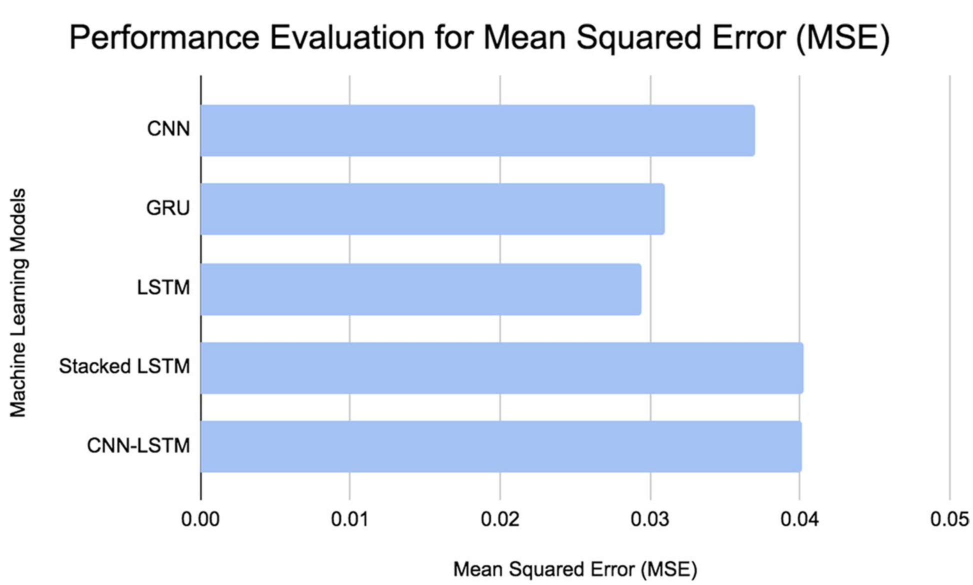


Fig. 5 Performance evaluation of machine learning models (MSE)

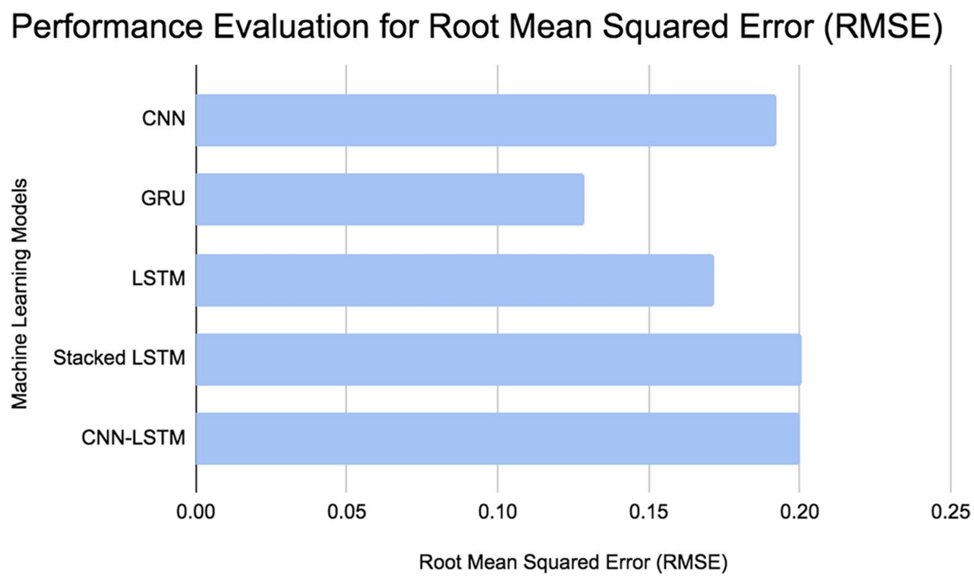


Fig. 6 Performance evaluation of machine learning models (RMSE)

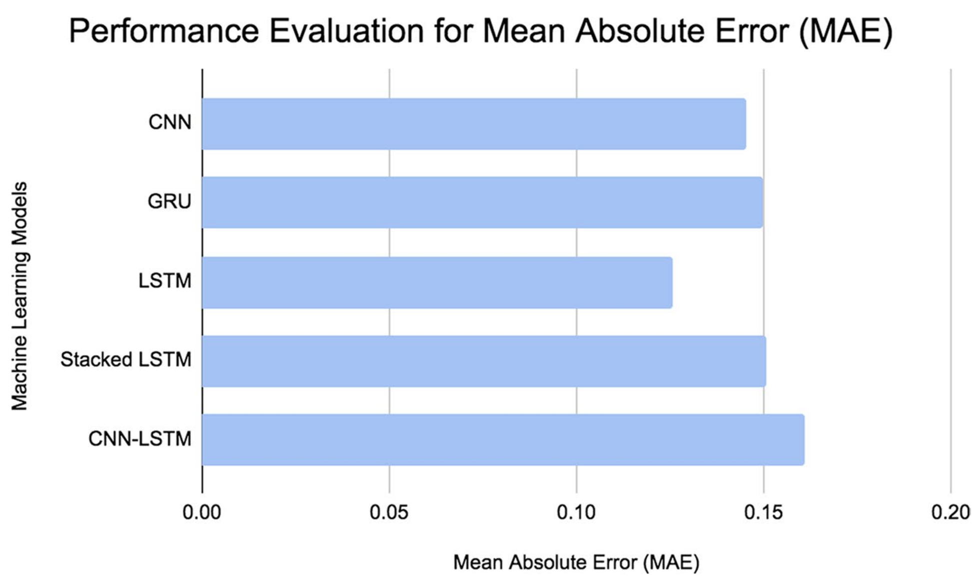


Fig. 7 Performance evaluation of machine learning models (MAE)

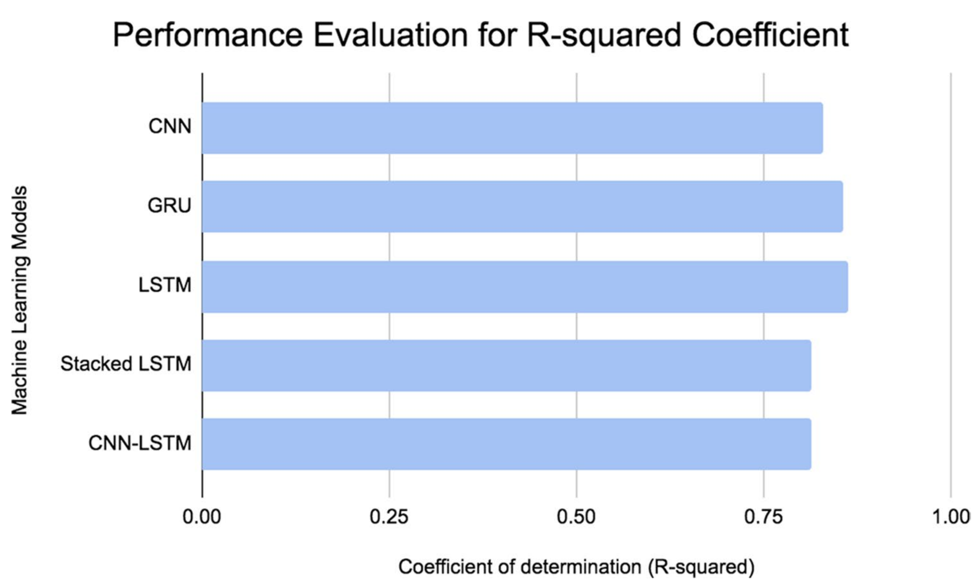


Fig. 8 Performance evaluation of machine learning models (MAE)

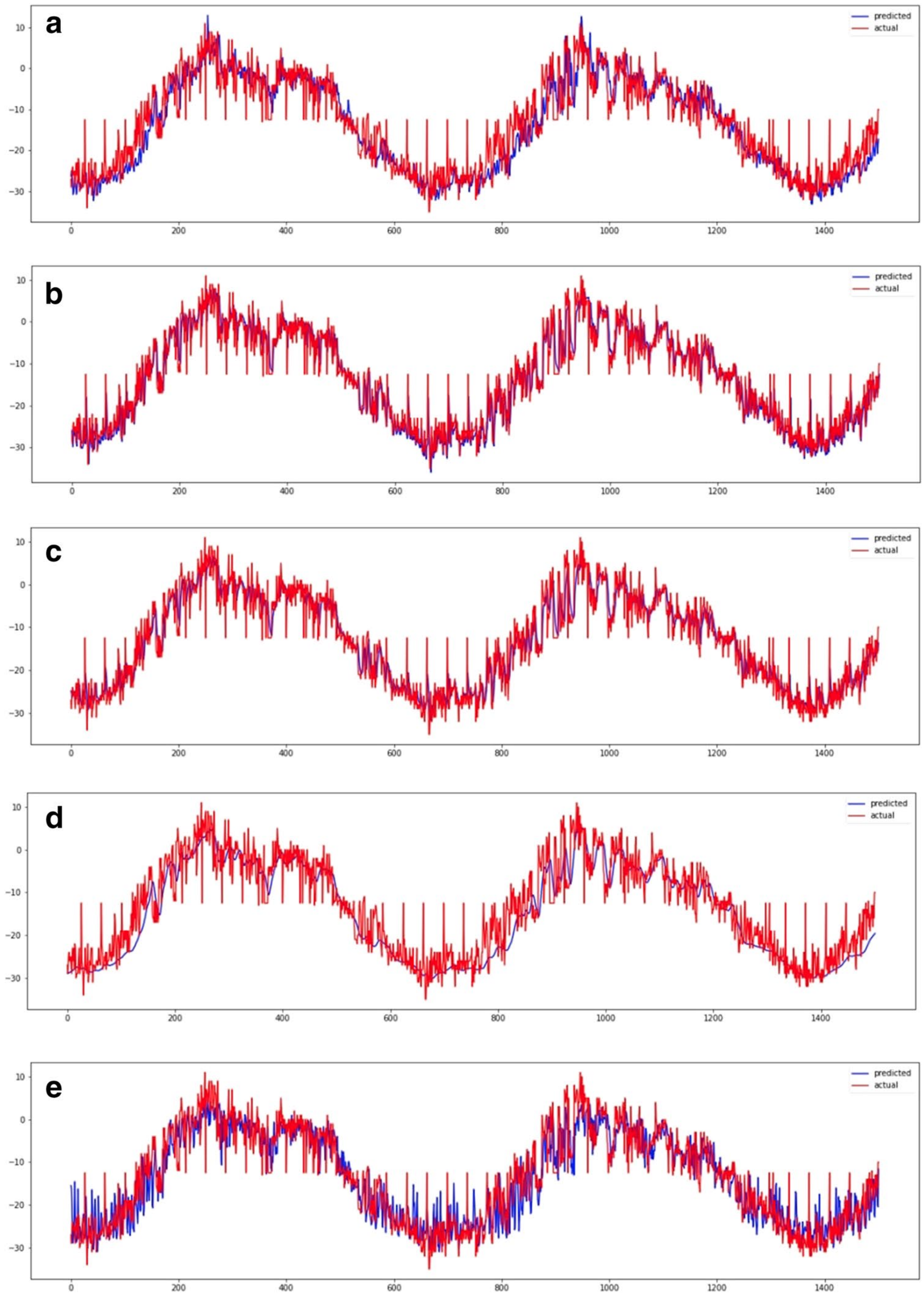


Fig. 9 **a** Predicted vs. actual plot for CNN model. **b** Predicted vs. actual plot for GRU model. **c** Predicted vs. actual plot for LSTM Model. **d** Predicted vs. actual plot for stacked LSTM model. **e** Predicted vs. actual plot for CNN-LSTM model

Figure 7 determines the performance evaluation of the machine learning models based on MAE. As we can see LSTM has the lowest value while CNN-LSTM has the highest value.

Figure 8 determines the performance evaluation of the machine learning models based on R-squared coefficient. As we can see LSTM has the highest value while stacked LSTM has the lowest value. Based on all these performance evaluation parameters and results, it is evident that LSTM is the most efficient model for analyzing Mars weather data in the study.

In order to validate our claim, we also present an illustration depicting a plot of predicted vs. actual values.

Figure 9a - e represents different models predicted vs. actual output. Red line and blue line represent the actual output and predicted output respectively. We observe that the predicted data points are almost overlapped by the actual data points in most of the cases. However in the case of CNN-LSTM, CNN, stacked LSTM and GRU,

Table 3 Comparative analysis of the proposed work

Year and author	Proposed work	Methodology/ Parameters	Results
Kass et al. 2020	Exploring Mars climate (Dust Storms)	Mars Climate Sounder recorded events	Global dust events report 50-Pa zonal tropical temperatures > 220 K .Regional dust storm does not exceed 205 K
Connour et al. 2020	A water-ice-cloud feature observed due to dust storms	Twilight cloud bands observed by the MAVEN/IUVS instrument	Expanded over 6000 km, and reached altitudes of 40 to 50 km
Le Maistre 2020	To compute the Mars troposphere errors	Surface pressure, mapping function, calibrating Doppler data	Mars troposphere contribution found to be < 1 % (RISE data), < 2 % (Opportunity data), < 2.5 % (Pathfinder data)
Eltahan et al. 2020	Temperature forecast over Mars at Jezero Crater landing site	Sensitivity of different optimization solvers in LSTM	Lowest RMSE predicts temperature between 34–36 martian years
Luginin et al. 2020	Studying the properties of water, ice and dust on the Martian atmosphere	Atmospheric Chemistry Suite (ESA-Roscosmos Trace Gas Orbiter mission)	Radius of dust and water ice particles lies between 0.1 − 3.5 μm and 0.1–5.5 μm, dust storms may reach altitudes of 85 km
Our proposed work, 2021	Analyzing Mars weather data using Machine Learning techniques	ML algorithms such as CNN, RNN, LSTM, stacked CNN, stacked LSTM, proposed CNN-LSTM model	The LSTM model outperforms other ML models with MSE = 0.0294, RMSE = 0. 1716, MAE = 0.1257, R-square = 0.8640

the overlapping is less evident as compared to LSTM. In LSTM, there is a better overlap of predicted values with respect to actual values which is indicative of the fact that the LSTM model is indeed the most robust model of all the models considered.

Comparative analysis

The following table (Table 3) depicts an overall comparative analysis of our proposed work with previous related works.

Based on the comparative analysis, we observe that most of the past research works done for analyzing the Martian atmosphere have been based on observations. These observations are usually obtained from orbiter missions, instruments and data. We analyze these observations in yet another way, i.e. using machine learning techniques. Based on our study, we successfully analyze Mars weather data using several algorithms and evaluate these using multiple performance evaluation parameters. The LSTM model performs better than the other baseline models considered for the study.

Conclusion and future work

The red planet has always been a subject of curiosity to researchers. Whether it is the presence of water on the planet or the possibility of creating a habitable environment, researchers and visionaries have always taken a keen interest in the plane Mars. Over the last few years, there has been intense research on exploring the Martian atmosphere. The planet is often seen as the potential habitat for humans following a colonization. Thus, analyzing the weather on the planet is necessary. In this paper we explore Mars weather data using several machine learning algorithms. The baseline algorithms considered for the study are CNN, GRU, LSTM, stacked LSTM, and CNN-LSTM. We evaluated all the models using performance evaluation metrics like RMSE, MAE, MSE and R-square. Our study depicts that the LSTM model conveniently outperforms all the other models.

In the future, we would like to identify more of these robust models that can assist us in exploring Martian weather. We would also like to identify more such conditions that may contribute to sustainability over the planet.

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Declarations

We declare that this manuscript is original, has not been published before, and is not currently being considered for publication elsewhere.

Conflicts of interest The authors declare no conflict of interest.

Consent to participate NA.

Ethics approval NA.

References

Albawi S, Mohammed TA, Al-Zawi S (2017) Understanding of a convolutional neural network. In:2017International Conferenceon Engineering and Technology (ICET). IEEE, New York, pp 1–6

Bak EN, Zafirov K, Merrison JP, Jensen SJK, Nørnberg P, Gunnlaugsson HP, Finster K (2017) Production of reactive oxygen species from abraded silicates. Implications for the reactivity of the Martian soil. Earth Planet Sci Lett 473:113–121

Banfield D, Spiga A, Newman C, Forget F, Lemmon M, Lorenz R, Banerdt WB (2020) The atmosphere of Mars as observed by InSight. Nat Geosci 13(3):190–198

Bibring JP, Langevin Y, Poulet F, Gendrin A, Gondet B, Berthé M, Schmitt B (2004) Perennial water ice identified in the south polar cap of Mars. Nature 428(6983):627–630

Charalambous C, Stott AE, Pike T, McClean JB, Warren T, Spiga A, Banfield D, Garcia RF, Clinton JF, Stähler S, Simon C et al (2021) A comodulation analysis of atmospheric energy injection into the ground motion at InSight, Mars. J Geophys Res Planets

Chung J, Gulcehre C, Cho K, Bengio Y (2015) Gated feedback recurrent neural networks. In: International conference on machine learning. PMLR, pp 2067–2075

Connour K, Schneider NM, Milby Z, Forget F, Alhosani M, Spiga A, ... Wolff MJ (2020) Mars's twilight cloud band: A new cloud feature seen during the Mars Year 34 global dust storm. Geophys Res Lett 47(1):e2019GL084997.

Dansana D, Kumar R, Adhikari JD, Mohapatra M, Sharma R, Priyadarshini I, Le DN (2020) Global forecasting confirmed and fatal cases of COVID-19 outbreak using autoregressive integrated moving average model. Front Public Health 8

Eltahan M, Moharm K, Daoud N (2020) Sensitivity of different optimization solvers in LSTM algorithm for temperature forecast over Mars at Jezero Crater landing site. In: 2020 21st International Arab Conference on Information Technology (ACIT). IEEE, New York, pp 1–5

Giuranna M, Wolkenberg P, Grassi D, Aronica A, Aoki S, Scaccabarozzi D, Formisano V (2021) The current weather and climate of Mars: 12 years of atmospheric monitoring by the Planetary Fourier Spectrometer on Mars Express. Icarus 353:113406

Gramigna E (2020) Calibration techniques for studying Venus and Mars atmospheres. Aerotecnica Missili & Spazio 99(4):255–261

Heavens NG, Kass DM, Kleinböhl A, Schofield JT (2020) A multiannual record of gravity wave activity in Mars's lower atmosphere from on-planet observations by the Mars Climate Sounder. Icarus 341:113630

Hochreiter S, Schmidhuber J (1997) Long short-term memory. Neural Comput 9(8):1735–1780

Holmes JA, Lewis SR, Patel MR (2020) OpenMARS: A global record of martian weather from 1999 to 2015. Planet Space Sci 188:104962

Jha S, Kumar R, Abdel-Basset M, Priyadarshini I, Sharma R, Long HV (2019) Deep learning approach for software maintainability metrics prediction. IEEE Access 7:61840–61855

Jha S, Kumar R, Chiclana F, Puri V, Priyadarshini I et al (2019) Neutrosophic approach for enhancing quality of signals. Multimed Tools Appl 1–32

Kannan KR (2020) Mars weather data. Retrieved February 28, 2021, from https://www.kaggle.com/imkrkannan/mars-weather-data

Kass DM, Schofield JT, Kleinböhl A, McCleese DJ, Heavens NG, Shirley JH, Steele LJ (2020) Mars Climate Sounder observation of Mars' 2018 global dust storm. Geophys Res Lett 47(23):e2019GL083931

Kereszturi A, Pal B, Gyenis A (2020) Temperature and humidity monitoring to identify ideal periods for liquefaction on Earth and Mars–data from the High Andes. Geol Q 64(4):898–914

Korablev O, Olsen KS, Trokhimovskiy A, Lefèvre F, Montmessin,FFedorova A, Toplis M, Alday J, Belyaev D, Patrakeev A, Ignatiev N, Shakun A, Grigoriev A, Baggio L, Abdenour I, Lacombe G, Ivanov Y, Aoki S, Thomas I, Daerden F, Ristic B, Erwin J, Patel M, Bellucci G, Lopez-Moreno J, Vandaele AC (2021) Transient HCl in the atmosphere of Mars. Sci Adv 7(7):eabe4386

Kruss M, Musiolik G, Demirci T, Wurm G, Teiser J (2020) Wind erosion on Mars and other small terrestrial planets. Icarus 337:113438

Lauro SE, Pettinelli E, Caprarelli G, Guallini L, Rossi AP, Mattei E, Orosei R (2021) Multiple subglacial water bodies below the south pole of Mars unveiled by new MARSIS data. Nat Astron 5(1):63–70

Le Maistre S (2020) Martian lander radio science data calibration for Mars troposphere. Radio Sci 55(12):1–16

Le Mouélic S, Caravaca G, Mangold N, Wright J, Carli C, Altieri F, Zambon F, Van Der Bogert C, Pozzobon R, Massironi M et al (2020) Using virtual and augmented reality in planetary imaging and mapping-a case study, vol 14. Europlanet Science Congress

Le Cun Y (2015) LeNet-5, convolutional neural networks. 20(5):14 http://yann.lecun.com/exdb/lenet. Accessed 15 Apr 2021

Leovy C (2001) Weather and climate on Mars. Nature 412(6843):245–249

Livieris IE, Pintelas E, Pintelas P (2020) A CNN–LSTM model for gold price time-series forecasting. Neural Comput Appl 32(23):17351–17360

Lorenz RD, Lemmon MT, Maki J, Banfield D, Spiga A, Charalambous C, ... Banerdt WB (2020) Scientific observations with the In Sight solar arrays: Dust, clouds, and eclipses on Mars. Earth Space Sci 7(5):e2019EA000992

Luginin M, Fedorova A, Ignatiev N, Trokhimovskiy A, Shakun A, Grigoriev A, Patrakeev A, Montmessin F, Korablev O (2020) Properties of water ice and dust particles in the atmosphere of Mars during the 2018 global dust storm as inferred from the Atmospheric Chemistry Suite. J Geophys Res: Planets 125(11):e2020JE006419

Martire L, Garcia RF, Rolland L, Spiga A, Lognonné PH, Banfield D, Martin R (2020) Martian infrasound: Numerical modeling and analysis of InSight's data. J Geophys Res: Planets 125(6):e2020JE006376

Medsker L, Jain LC (1999) Recurrent neural networks: design and applications. CRC Press, Boca Raton, FL

Ordonez-Etxeberria I, Hueso R, Sánchez-Lavega A, Vicente-Retortillo Á (2020) Characterization of a local dust storm on Mars with REMS/MSL measurements and MARCI/MRO images. Icarus 338:113521

Patro SGK, Mishra BK, Panda SK, Kumar R, Long HV, Taniar D, Priyadarshini I (2020) A Hybrid Action-Related K-Nearest Neighbour (HAR-KNN) approach for recommendation systems. IEEE Access 8:90978–90991

Pritam N, Khari M, Kumar R, Jha S, Priyadarshini I, Abdel-Basset M, Long HV (2019) Assessment of code smell for predicting class change proneness using machine learning. IEEE Access 7:37414–37425

Priyadarshini I (2018) Features and architecture of the modern cyber range: aqualitative analysis and survey (Doctoral dissertation, University of Delaware)

Priyadarshini I, Cotton C (2020) Intelligence in cyberspace: the road to cyber singularity. J Exp Theor Artif Intell 1–35

Priyadarshini I, Cotton C (2021) A novel LSTM–CNN–grid search-based deep neural network for sentiment analysis. J Supercomput 1–22

Priyadarshini I, Mohanty, PR Cotton C (2021) Analyzing some elements of technological singularity using regression methods. Comput Mater Continua 67(3):3229–3247

Priyadarshini I, Puri V (2021) A convolutional neural network (CNN) based ensemble model for exoplanet detection. Earth Sci Inform :1–13

Puri V, Jha S, Kumar R, Priyadarshini I, Abdel-Basset M, Elhoseny M, Long HV (2019) A hybrid artificial intelligence and internet of things model for generation of renewable resource of energy. IEEE Access 7:111181–111191

Quek SG, Selvachandran G, Munir M, Mahmood T, Ullah K, Son LH, Priyadarshini I (2019) Multi-attribute multi-perception decision-making based on generalized T-spherical fuzzy weighted aggregation operators on neutrosophic sets. Mathematics 7(9):780

Rogberg P, Read PL, Lewis SR, Montabone L (2010) Assessing atmospheric predictability on Mars using numerical weather prediction and data assimilation. Q J R Meteorol Soc 136(651):1614–1635

Rokbani N, Kumar R, Abraham A, Alimi AM, Long HV, Priyadarshini I et al. (2020) Bi-heuristic ant colony optimization-based approaches for traveling salesman problem. Soft Comput 1–20

Sharma R, Kumar R, Sharma DK, Priyadarshini I, Pham BT, Bui DT, Rai S (2019) Inferring air pollution from air quality index by different geographical areas: case study in India. Air Qual Atmos Health 12(11):1347–1357

Szantai A, Audouard J, Forget F, Olsen KS, Gondet B, Millour E, Bibring JP (2021) Martian cloud climatology and life cycle extracted from Mars Express OMEGA spectral images. Icarus 353:114101

Tan J, Sephton MA (2020) Organic records of early life on Mars: The role of iron, burial, and kinetics on preservation. Astrobiology 20(1):53–72

Tuan TA, Long HV, Kumar R, Priyadarshini I, Son NTK (2019) Performance evaluation of Botnet DDoS attack detection using machine learning. Evolutionary Intelligence, pp 1–12

Vo T, Sharma R, Kumar R, Son LH, Pham BT, Bui TD, Priyadarshini I, Sarkar M, Le T (2020) Crime rate detection using social media of different crime locations and Twitter part-of-speech tagger with Brown clustering. J Intell Fuzzy Syst (Preprint) 1–13

Yang R, Singh SK, Tavakkoli M, Amiri N, Yang Y, Karami MA, Rai R (2020) CNN-LSTM deep learning architecture for computer vision-based modal frequency detection. Mech Syst Signal Process 144:106885