Predicting Variation in Daily Martian Atmospheric Temperature Using Machine Learning Techniques.

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Abstract
According to research and explorations conducted on mars. It was believed that the planet once supported life. This resulted from some evidence indicating the presence of water and a thick warm atmosphere on mars in the past. Due to this, man became curious to explore the planet as the red planet is believed to be similar to earth. Many technological tools have evolved with advancements in science and technology, making the entire exploration mission easy. Machine learning standout to be an essential technical tool today that is in use for mars exploration. Although the field is new, little work has been done in exploring mars' weather patterns for possible habitation of life. This work relied on the strength of machine learning techniques to analyse the mars data obtained from the EMM EMIRS instrument database. In this work, various techniques such as exploration, pre-processing, model development, and evaluations were performed on the dataset to predict the variation in daily atmospheric temperatures of mars present within the dataset. Seven machine learning models were developed in this work: Random Forest, Linear regression, SVM, ANN, CNN, Lasso Regression and Decision tree. The developed models were subjected to hyperparameters fine-tuning their accuracies. Finally, each model was evaluated using RMSE, MAE, and R2 value evaluation techniques. Following the evaluation, random forest outperformed all other six models used in this work with scores as follows: RMSE=1.5525, MSE=2.4105, MAE=1.1939 and R2=0.8283. Finally, the scores obtained were visualised.

Keywords: Mars, space exploration, Models, Python, NASA, EMIRS, EMM, evaluation, pre-processing .

Introduction:
Scientists oldest guess is that life existed on this planet because of its nature resembling Earth (Chang K., 2013). In a quest for knowledge, mankind has used diverse space exploration technology to conduct research on other planets to determine the presence or otherwise of life. To this exploration, planet mars are deemed to be a planet that has potential life. Planet mars can in fact viewed directly from the earth as it is colored red hence being referred to as the Red Planet (Charles et al. al 2022). The phenomenon which makes Mars an appearance of reddish hue is due to the existence of oxidized iron on the surface of the planet. However, current programs like sending rovers to mars and getting the data about the Martian weather are effective but one of the most important factors – variable Martian weather – still has to be further investigated. The goal of this study is to build a model that could forecast fluctuations in atmospheric temperature on Mars during a day. The model will be trained and the accuracy tested using data

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used. All this contributes to existing data available on Martian atmosphere implying that the results will play a significant role in offering fresh insight on climate on the red planet. Research in the subject and conditions of the Martian climate has been a matter of interest to scientist and researchers for several decades now. Mars is exceptional in that it provides vary climate and climate is important for manned and robotic missions that may occur in the planet's future as well as to examine for any effects. Mars like other planets has different kinds of weather and one of it is diurnal variation of temperature. This variation, which happens over a day, is an important part of weather on Mars and could give valuable information about the forces that drive this planet's weather. For these insights, the variations have been provided by means of machine learning techniques. This can be realised through the generation of models.

Even though much has been written about the Martian climate and research has gone far in identifying this variation in daily atmospheric temperature the current models are not precise enough. The current models used in the prediction of weather on Mars are from empirical correlations, and are dependent on limited data (Ishaani P. and Puri V. 2021; Ali M 2021). Therefore, these models lack the sophistication and versatility needed to describe how multiple atmospheric parameters are interconnected and how they affect the surface of a planet.

Literature review:

This article focuses on the literature review of utilizing machine learning (ML) for the prediction of weather on Mars by highlighting the ML application's extent because of the exhaustive Martian weather conditions and the consequences it will have on future Martian missions. Scientists have rampantly employed ML in areas of weather, Bellutta (2017) independently implemented ANN in defining the opacity of Martian atmosphere. Gravity waves on Mars were investigated by Kass et al. (2020) with Mars Climate Sounder, while Mars' weather using ML models was examined by Ishaani and Puri (2021); the best model was identified as LSTM. Alejandro de C. G. et al. (2019) applied ANN in order to estimate the sol pressure and air temperature on Mars per hour with great accuracy. They include Charalambous et al. (2021) and Olsen et al. (2021), who researched seismic and geophysical activity towards assessment of environmental information on Mars. Also, P.N. Timothy (2022) pointed the significance of the ML in Martian science and called for data to be driven. However, the review finds some of these questions still remaining unanswered including the need to develop advanced models of weather prediction on Mars. This paper concludes that more research and the use of Ml are needed to enhance awareness and readiness for future Mars landings. To achieve this goal, this research uses several machine learning algorithms to make predictions of the atmospheric conditions on Mars especially atmospheric temperature. These include: Random Forest: A technique that builds a set of decision trees and makes use of them to make the class/label predictions for classification and numerical values for regression. Specially to deal with the problem of data imbalance, it works as policies and make predictions by calculating the mode of each tree for classification and mean for regression. Lasso Regression: A regularization technique that put a penalty on the model parameters, collapsing regression coefficients for certain variables towards zero, and therefore, selects the most significant predictors. Decision Tree: Tree-based structures, where data is modelled by nodes and involves the impactful correlation of features and target variables. It is easily understandable and applicable for interval or ratio level and nominal or ordinal data.

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Artificial Neural Network (ANN): A computational model containing a set of algorithms based on the human brain and task-specific patterns or features extracted from input data. ANNs are learning tools that work from example data and are specifically good at making predictions based on some input data.

Support Vector Machine (SVM): A type of learning algorithm that has a supervisory signal in the training data or feature set and falls under the classification category. It makes an nth dimensional plane or decision surface so as to classify the data into different classes/regions.

Linear Regression: A type of supervised learning method that predicts the dependent variables by making a regression of straight line.

Convolutional Neural Network (CNN): This type of CNN was originally developed with image classification in mind but can nevertheless be used in non-image inputs as well. Cortical Computing Corp has developed technology to search for patterns in large sets of data using a deep learning architecture mimicking brain connectivity. Also, the features of the Emirates Mars Infrared Spectrometer (EMIRS) are described. Spearheaded in 2020, EMIRS will investigate the atmosphere of Mars particularly the thermal, dust, water vapor, and ice. This was developed in partnership with Arizona State University and the Mohammed Bin Rashid Space Centre to help study Mars' lower and middle atmospheric layer during EMS.

Methodology

3.1 Dataset Used

The dataset for this research was obtained from the Emirates Mars Mission (EMM) official website. Specifically, data from the *Emirates Mars Infrared Spectrometer (EMIRS)* instrument was downloaded from the following source: EMM EMIRS Data.

The downloaded dataset was in Flexible Image Transport System (FITS) format, which is commonly used in astronomy to store data in array-like or table-like structures. To utilize the data for analysis, a Python script was written to extract the FITS files and convert them into CSV format for easier processing and analysis.

Strategies used to conduct analysis
The figure below shows the workflow followed to conduct proper analysis on the dataset to perform proper analysis on the Martian dataset used:

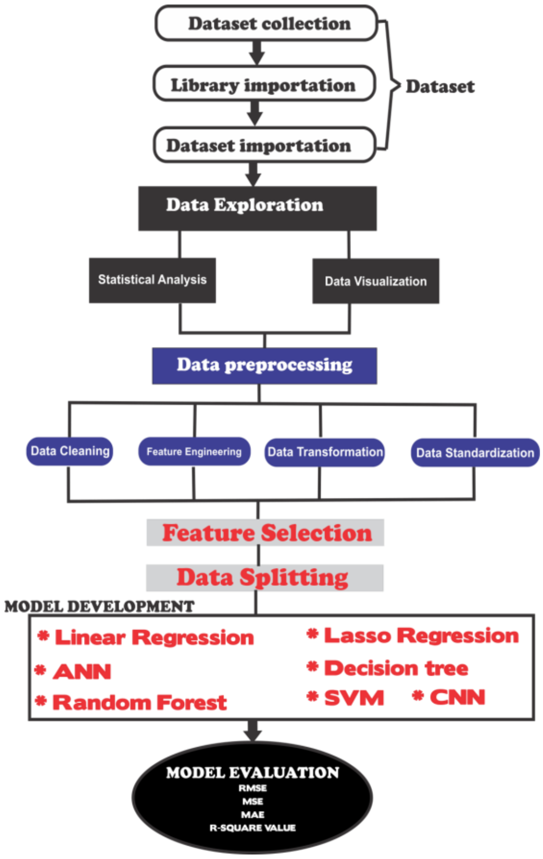

Fig. 1: workflow for Martian analysis

Data Preprocessing:

Data preprocessing improves the quality of raw data, making it suitable for machine learning models. It involves steps like data cleaning (removing or imputing missing values), outlier removal, normalization or standardization, and feature transformation. In this work, Python's Pandas library was used to apply these techniques. Preprocessing ensures that the model

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performs optimally by transforming and cleaning the dataset.

Data Exploration:

Data exploration is the initial phase of analysis, using statistical and visualization techniques to uncover patterns in the dataset. Tools like Pandas, NumPy, Matplotlib, and Seaborn were utilized in this report to understand Martian atmospheric temperature variations.

Feature Selection:

Selecting relevant features is critical for model performance. This report selected features such as pressure and various temperature metrics based on their correlation with the target variable (atmospheric temperature). Proper feature selection enhances the accuracy of predictions.

Models Deployment:

Seven machine learning models were deployed: Linear Regression, Random Forest, Decision Tree, Artificial Neural Networks, Lasso, Convolutional Neural Network (CNN), and Support Vector Machine (SVM). These models were trained and tested using an 80/20 data split to identify the best-performing model.

Data Splitting:

The dataset was divided into an 80% training set and a 20% testing set using Python's train_test_split function from the sklearn library. This step ensures that the models are trained and validated effectively.

Hyperparameter Fine-Tuning:

Hyperparameter tuning was performed using grid search to optimize model performance.

This step is essential to finding the best parameters that deliver the most accurate predictions.

Model Evaluation:

To evaluate model performance, techniques like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared were used. These metrics help measure how well the model predicts the target variable and identify underperformance.

Result Analysis And Discussion

4.1 Results obtained from Experiment conducted on variation in temperature.

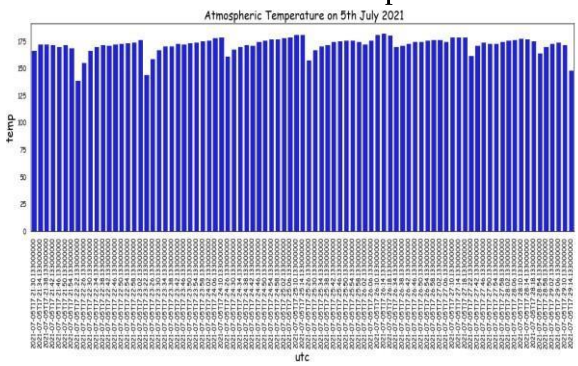

Fig. 19a: Atmospheric Temperature for 5th July 2021 (Bar chart)

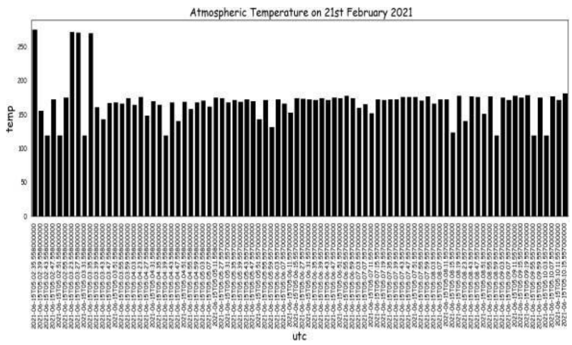

Fig. 19b: Atmospheric Temperature for 21st July 2021 (Bar chart)

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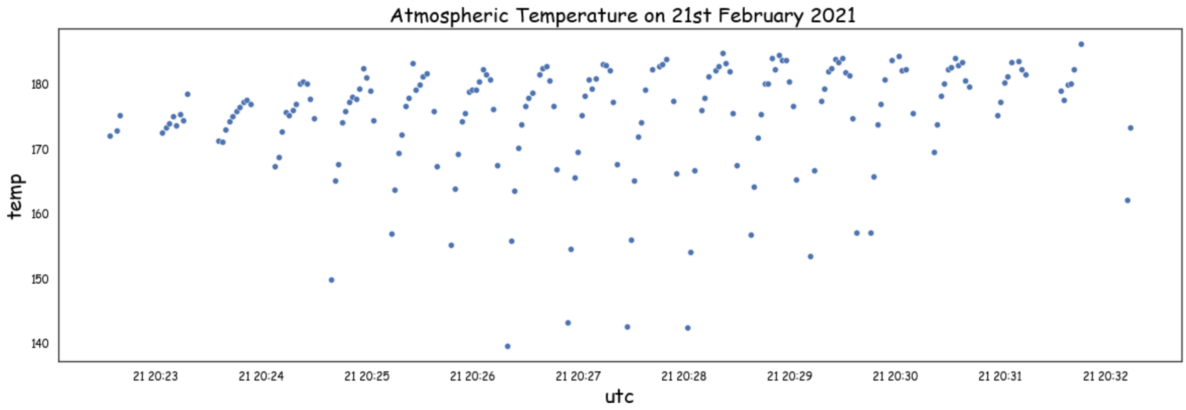

Fig. 19c: Atmospheric Temperature for 5th July 2021 (Scatter plot)

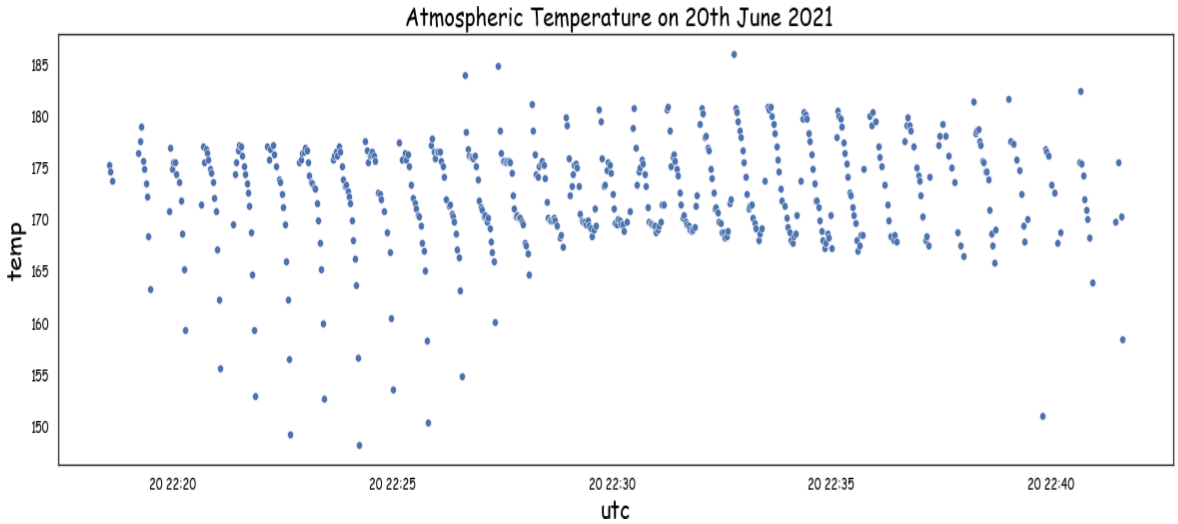

Fig. 19d: Atmospheric Temperature for 20th July 2021 (Scatter plot)

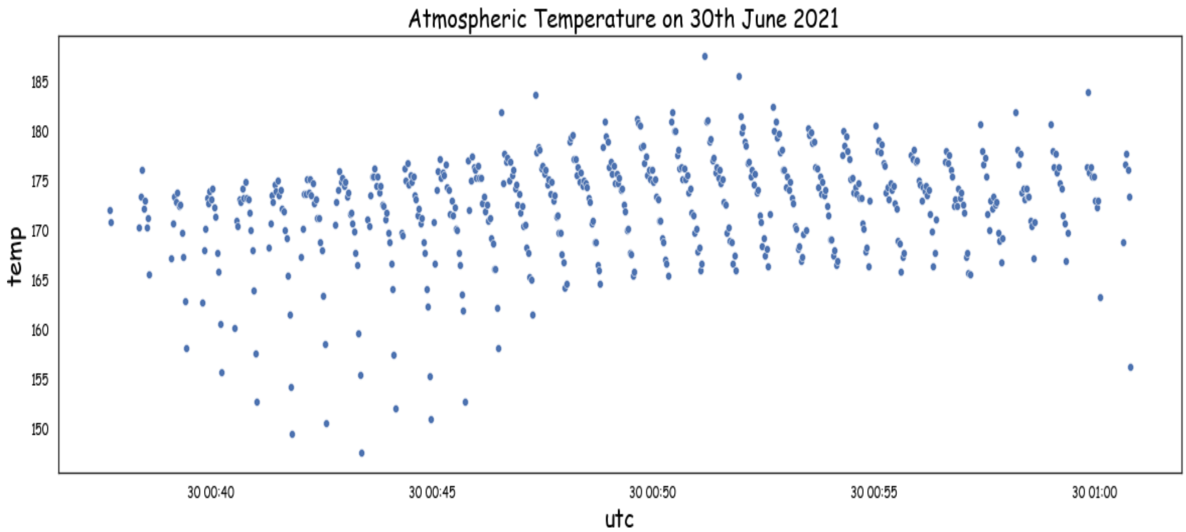

Fig. 19f: Atmospheric Temperature for 30th July 2021 (Scatter plot)

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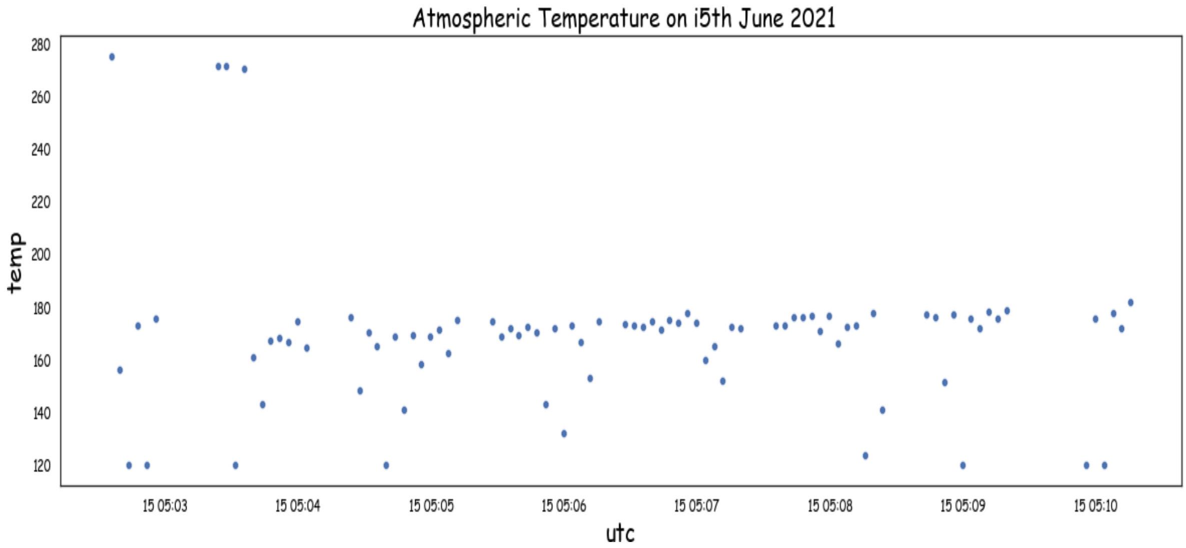

Fig. 19g: Atmospheric Temperature for 15th July 2021 (Scatter plot)

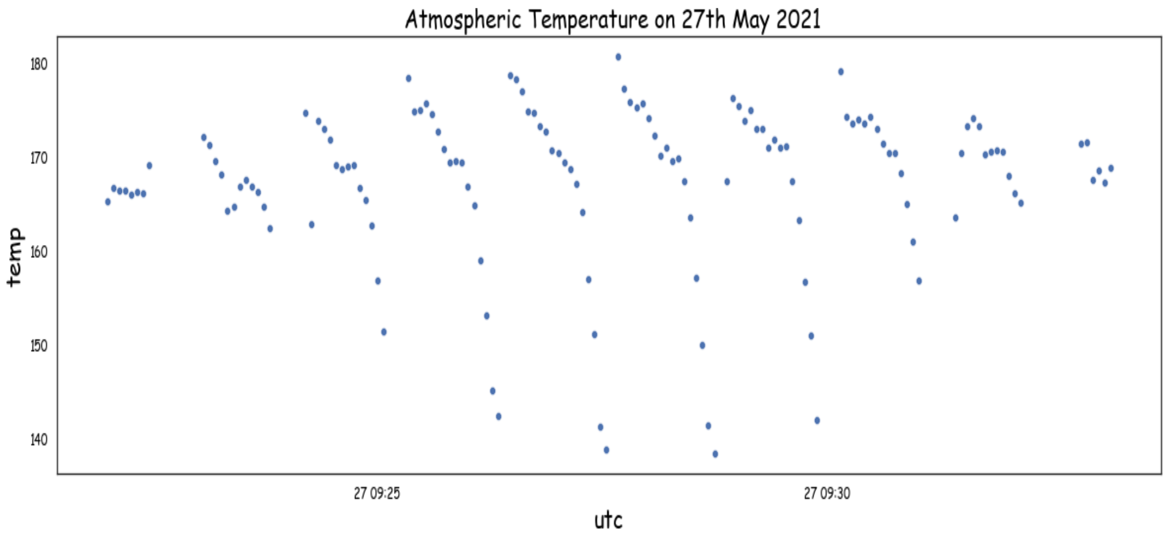

Fig. 19h: Atmospheric Temperature for 27th July 2021 (Scatter plot)

The above results were obtained from taking 6 days (I.e. sols) within the dataset and visualizing their atmospheric temperatures. From the above figures 16a-16h, it can be clearly seen that there is a variation in the daily temperature value for mars. From the figures, it can be observed that within a martian day, the temperature seems to be lower at early hours and higher at late hours. Although some days experience higher temperature values early hours compare to late hours e.g 21st and 15th July 2021. This is a clearly indication of diurnal variation in temperature of mars as presented by Dimitra A. et. al., 2023 and Michael D et. al, 2022.

This variation in mars temperature are largely sponsored by the amount of dust present in its
atmosphere. According to Royal Belgian institute for space Aeronomy (2022), variation in day and night temperature of mars is mainly due to the weakness of greenhouse effect which contributes to the Martian soil storing very few amounts of energy.

4.2 Results obtained from Experiment conducted for similarities among mars temperatures

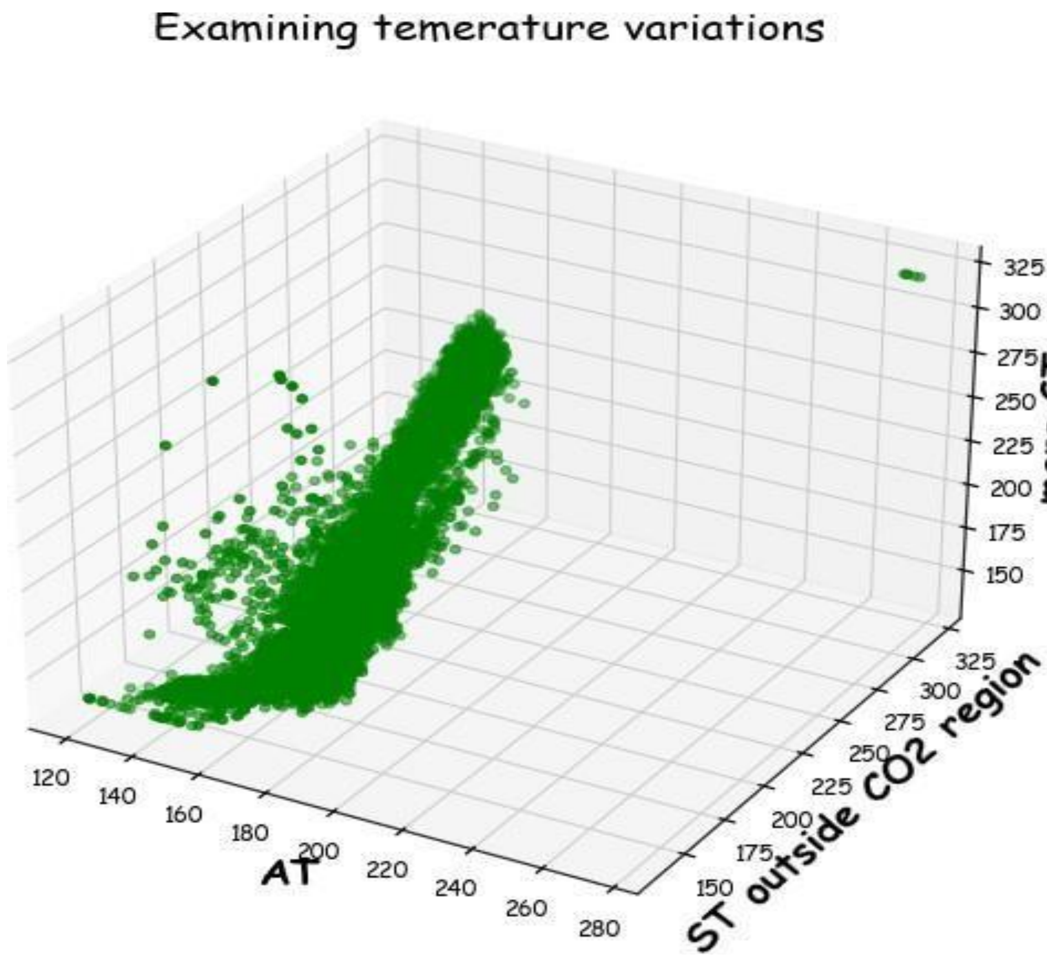

Fig. 20a: Relationship between AT, ST for CO2 and ST

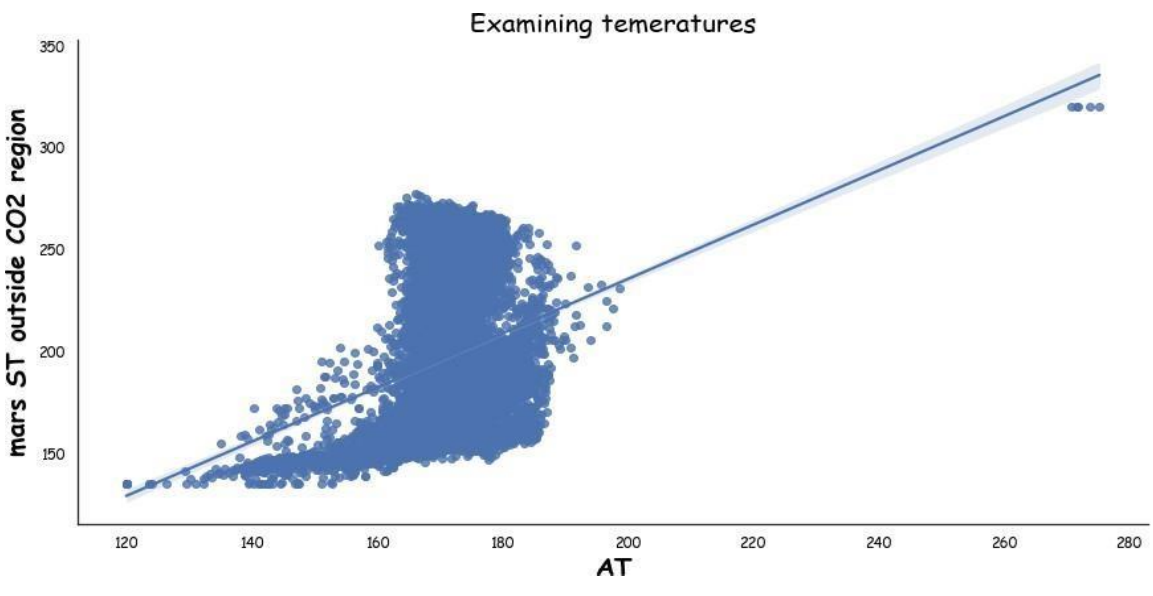

Fig. 20b: Linear Relationship between AT and ST outside CO2

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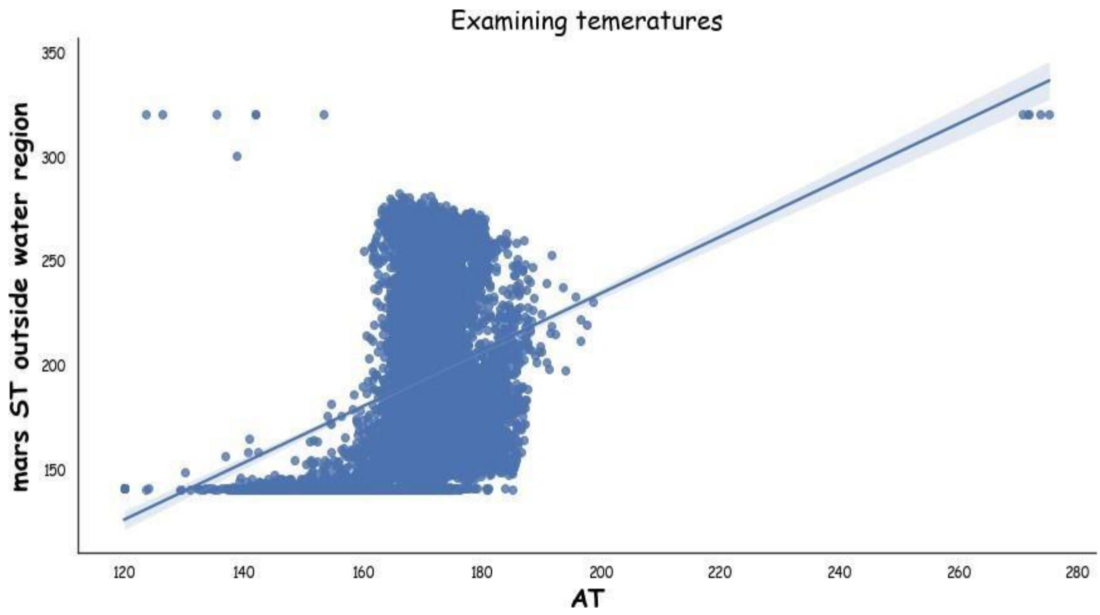

Fig. 20c: Linear Relationship between AT and ST for H2O

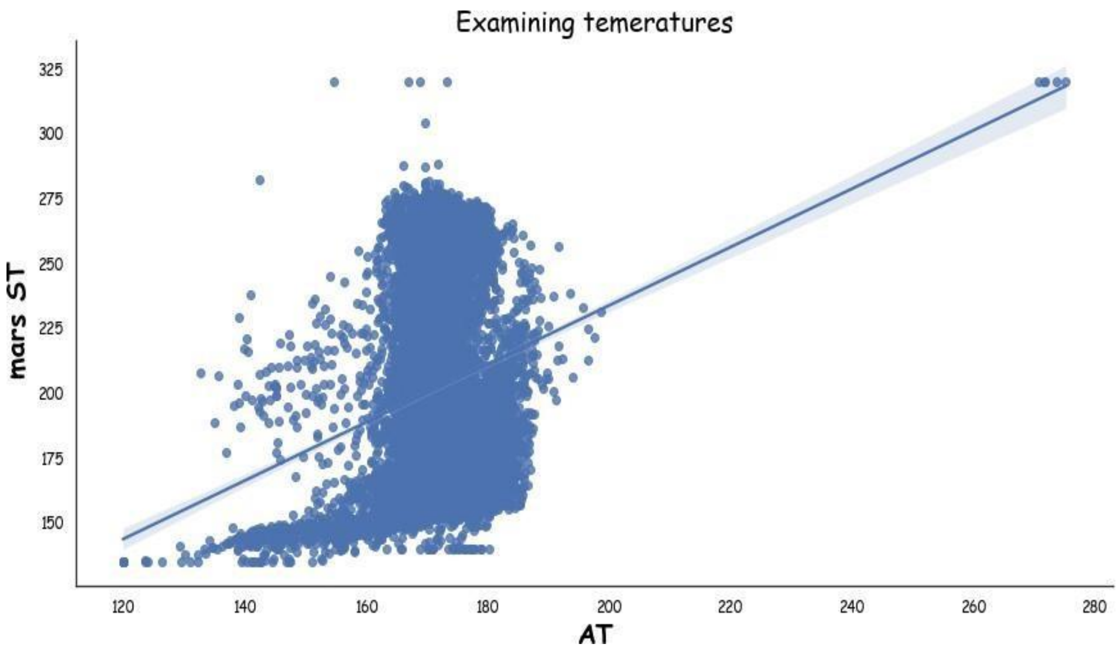

Fig. 20d: Linear Relationship between AT and ST in Mars

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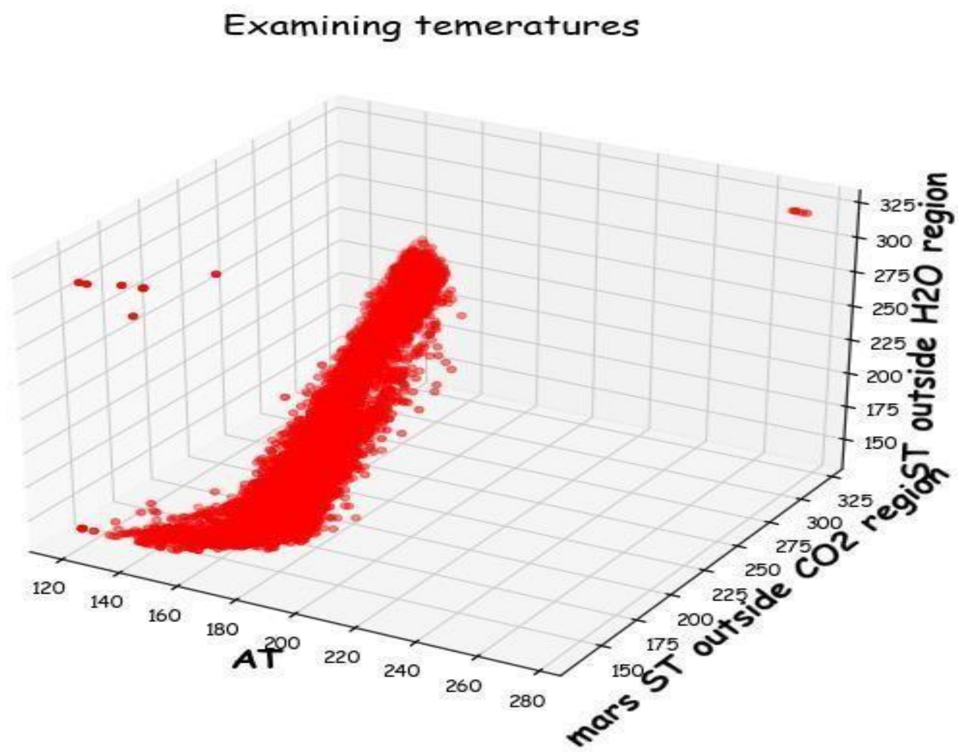

Fig. 20e: Relationship between AT, ST for CO2 and ST for H2O

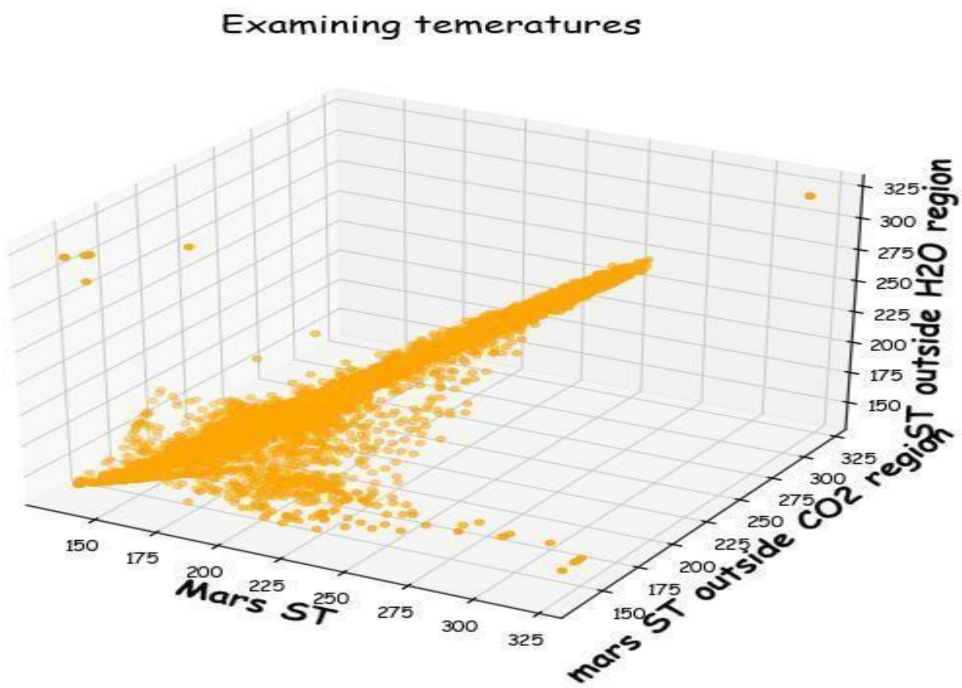

Fig. 20f: Relationship between ST, ST for CO2 and ST for H2O

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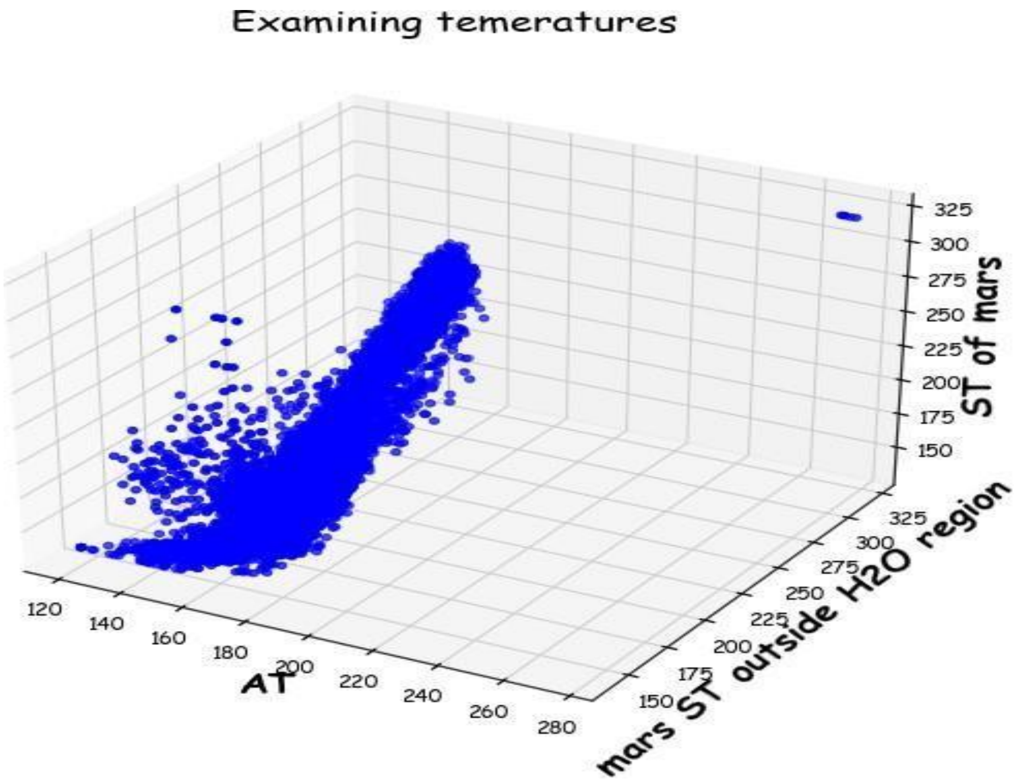

Fig. 20g: Relationship between AT, ST for H2O and ST.

The above results were generated by executing an experiment that was designed to test if correlation between all asserted temperature values of the EMIRS instrument holds true. Analyzing the results presented in Fig. 20a – Fig. 20g it is possible to identify the linear dependency of all the sorts of temperatures within the dataset under consideration. The EMIR instrument captured 4 temperature readings which are, Atmospheric temperature (AT), Surface Temperature(ST), Surface temperaure out of Water region (ST out of H2O) and Surface temp outside CO2 region(ST out of CO2). From the above results, these temperatures have an aspect of mutual coexistence as the various figures showed the existence of a linear relationship where data from one affects the other, as evidenced by the part where the different figures formed a linear relationship.

4.3 Results obtained from model development

For model development, two different experiments were conducted on the dataset. The first experiment was conducted without removing outliers present within the dataset while the second experiment removed outliers present within the dataset before model development. The results obtained from these two experiments are presented below:

4.3.1 Results from experiment without removal of outliers

The results below were obtained after models were developed without removal of outliers present within the dataset:

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Model	MAE	MSE	RMSE	R_2 score
Random forest	1.3179	4.1967	2.0486	0.9448
Linear Regression	3.4310	50.0191	7.0724	0.3423
Support Vector Machine (SVM)	3.3729	45.1238	6.7174	0.4067
Artificial Neural Network (ANN)	149.4879	22704.6600	150.6807	-297.5380
Decision Tree	1.4242	3.6380	1.9073	0.9521
LASSO regression	3.0438	18.8760	4.3447	0.7518
Convolutional neural Network (CNN)	166.4401	27810.7507	166.7656	-364.6769

Table 1: Result after removal of outliers

The above table presents the results obtained from development and evaluation of used machine learning models without handling outliers present within the dataset.

4.3.2 Results after handling outliers present within dataset

Model	MAE	MSE	RMSE	R_2 score
Random forest	1.1188	2.4228	1.5566	0.8275
Linear Regression	1.5275	3.5820	1.8926	0.7449
Support Vector Machine (SVM)	1.3887	3.9814	1.9953	0.7165
Artificial Neural Network (ANN)	31.6600	1530.9090	39.1268	-108.0029
Decision Tree	1.5839	5.1040	2.2592	0.6366
LASSO regression	2.0469	7.2166	2.6864	0.4862
Convolutional neural Network (CNN)	169.4396	28725.9820	169.4874	-2044.3299

Table 3: Result after removal of outliers

The results from two experiments on the EMIRS dataset are summarized in Tables 1 and 2. In Table 1, where outliers were not addressed, Random Forest and Decision Tree models achieved high R2 scores but exhibited large errors, indicating that the high R2 scores were influenced by overfitting. In contrast, Table 2 shows lower R2 scores but significantly reduced errors after outliers were removed, highlighting the importance of outlier removal in improving model accuracy. Neural networks (ANN and CNN) produced negative R2 scores and high errors, demonstrating their unsuitability for the dataset, as their predictions were worse than a simple mean prediction. Among the models tested, Random Forest outperformed the others by achieving minimal error values and a realistic, high R2 score, making it the best model for this

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dataset. The comparison of model performance is illustrated in the following figures.

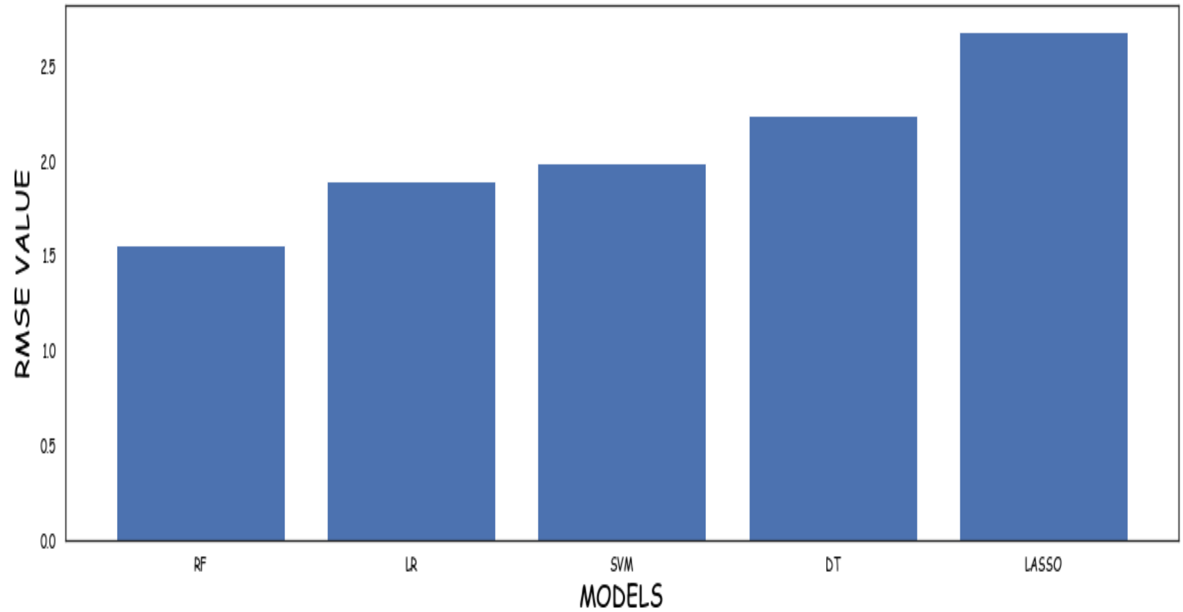

Fig. 21a: RMSE for the 5 models with high performance

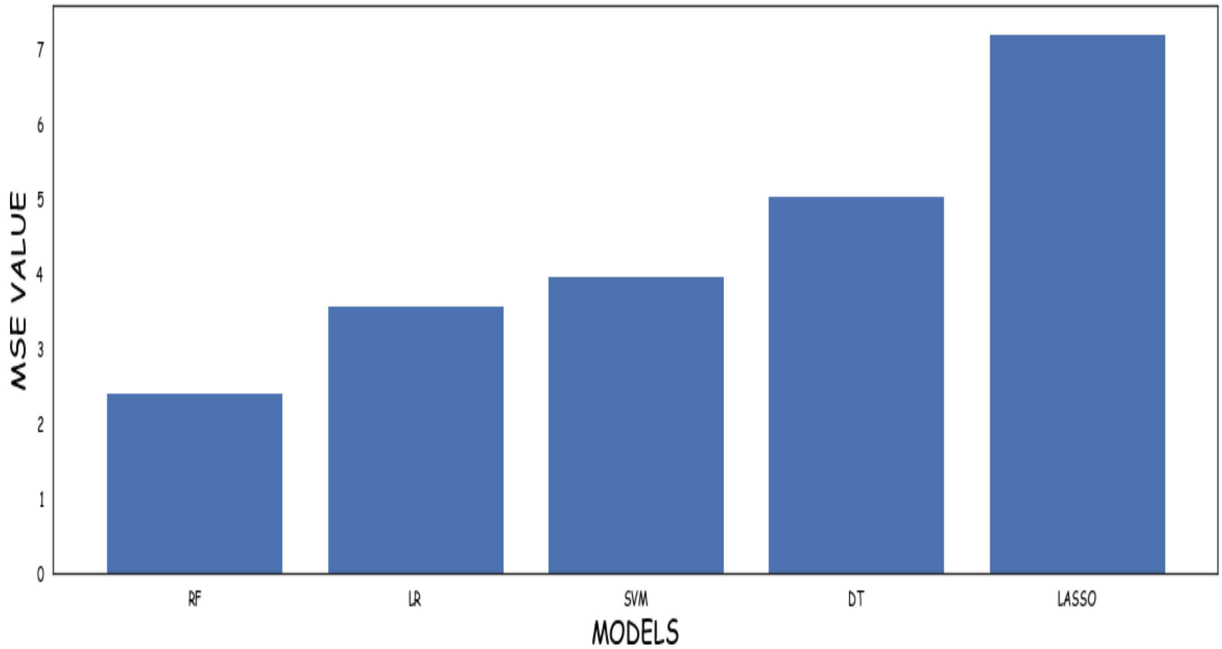

Fig. 21b: MSE for the 5 models with high performance

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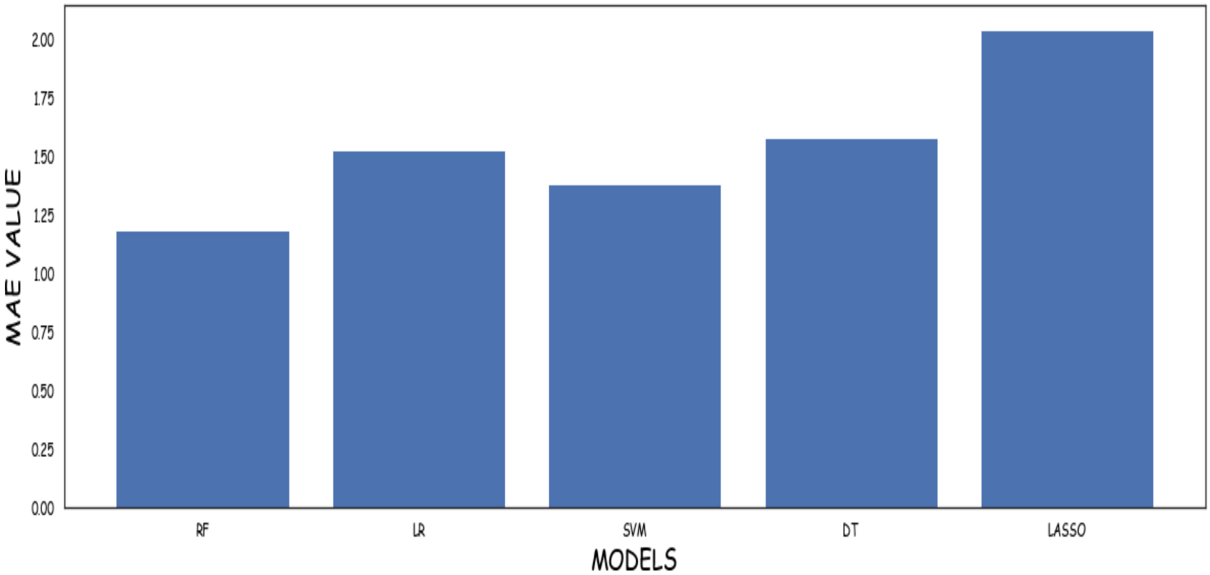

Fig. 21c: MAE for the 5 models with high performance

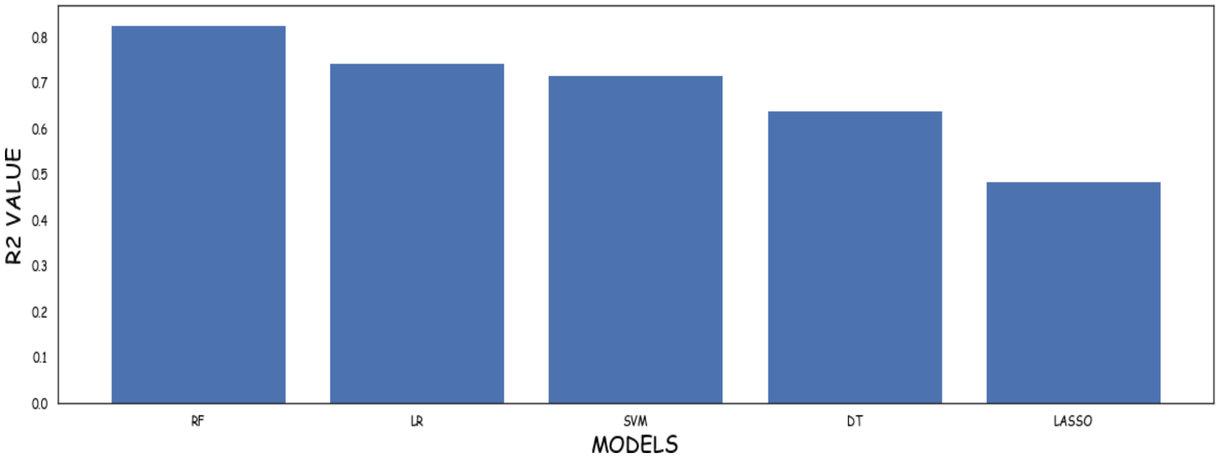

Fig. 21d: R2 Values for the 5 models with high performance

The high performance of Random Forest can be clearly seen across all 4 figures.

Due to this performance the 5 models were subject to hyper parameter fine tuning using GridsearhCV (Joseph R., 2018) and the results obtained are presented in Table 4 below:

Model	MAE	MSE	RMSE	R_2 score
Random forest	1.1939	2.4105	1.5525	0.8283
Linear Regression	1.5275	3.5819	1.8926	0.7449
Support Vector Machine (SVM)	1.5038	3.6944	1.9221	0.7369
Artificial Neural Network (ANN)	---------------	----------------	---------------	---------------
Decision Tree	1.5898	5.0146	2.2393	0.6429
LASSO regression	1.5271	3.5809	1.8923	0.7450
Convolutional neural Network (CNN)	--------------	-------------	--------------	--------------

Table 4: Result after Hyper parameter fine tuning

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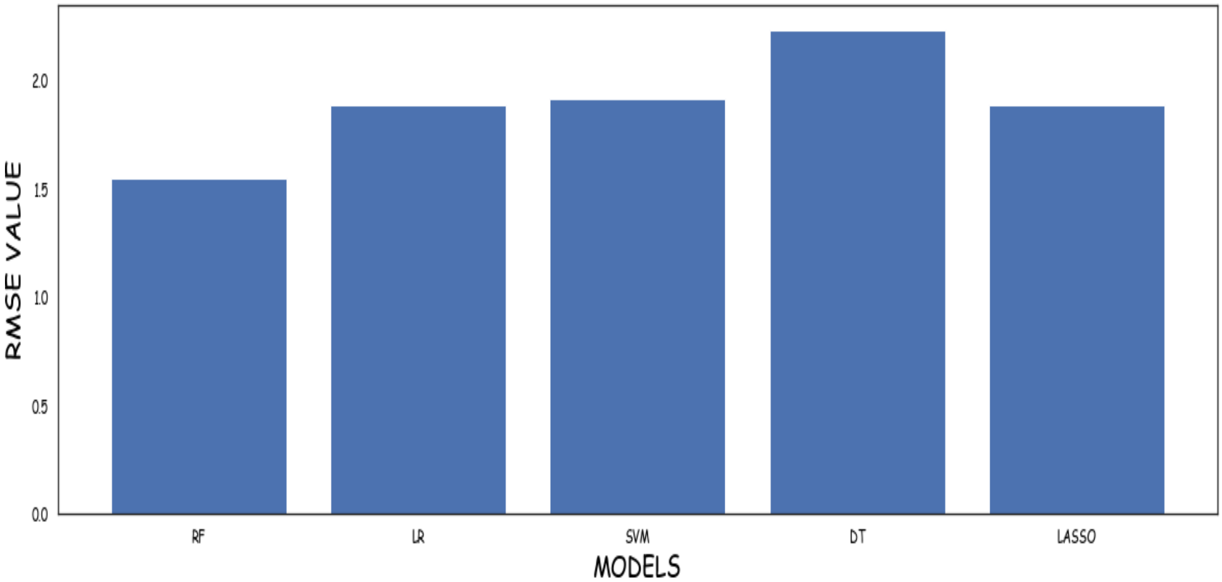

Fig. 22a: RMSE for the 5 models with high performance (After hyper parameter fine tuning)

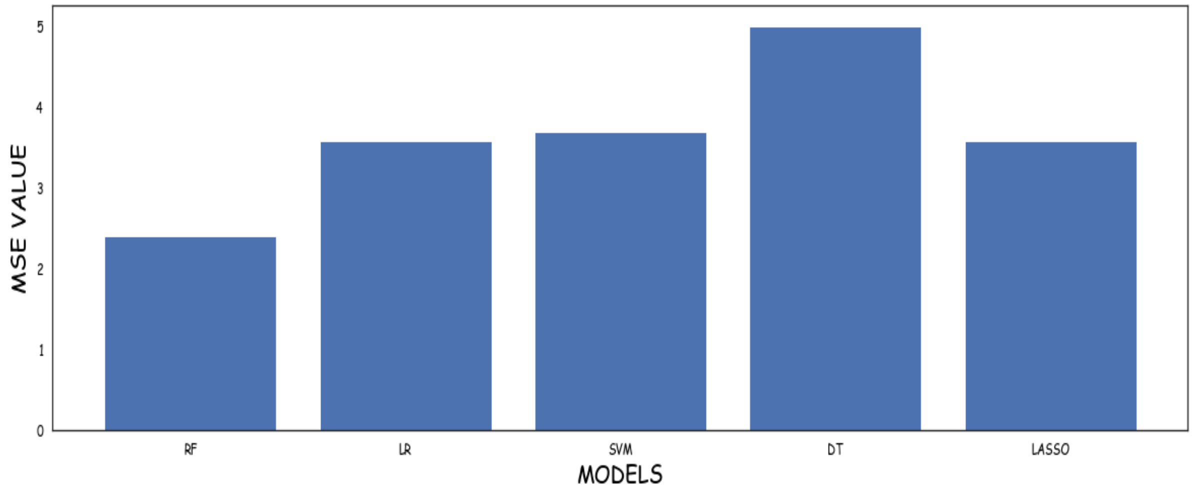

Fig. 22b: MSE for the 5 models with high performance (After hyper parameter fine tuning)

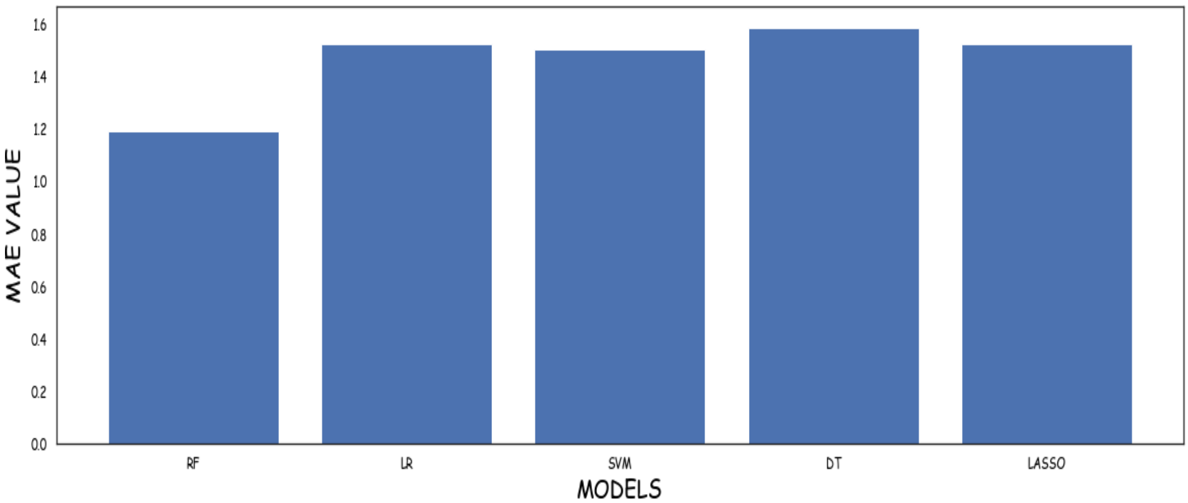

Fig. 22c: MAE for the 5 models with high performance (After hyper parameter fine tuning)

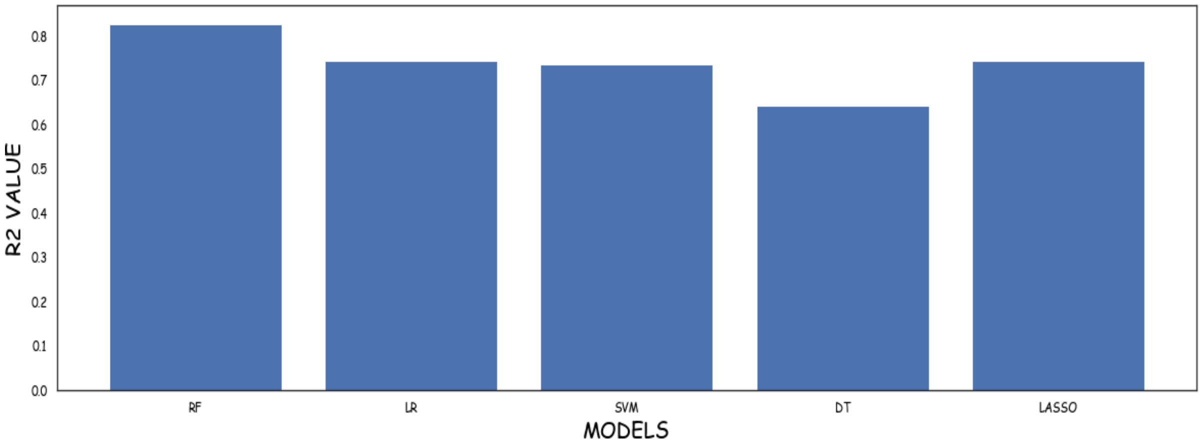

Fig. 22d: R2 Values for the 5 models with high performance (After hyper parameter fine tuning)

Table 4 and Figures 22a-22d illustrate the improved performance of the five models after hyperparameter fine-tuning. Random Forest, the best-performing model, showed notable improvements in terms of MSE, RMSE, and R2 scores. Compared to the earlier results in Figures 21a-21b and Table 3, the new results in Figures 22a-22b and Table 4 demonstrated better accuracies. Specifically, the MSE of the Random Forest model decreased by 0.0123, the RMSE decreased by 0.0041, and the R2 score increased by 0.0008. These improvements indicate that the hyperparameter tuning process was effective in optimizing the models' performance.

Critical Discussion Summary

In the present research, to model the daily Martian atmosphere temperature fluctuations, the EMM EMIRS dataset was analyzed employing seven machine learning algorithms in two experiments. While in the first experiment, models were developed with outliers still in the dataset, in the second experiment, the above defined outliers were removed from the dataset. The results obtained in the first experiment yielded higher R-squared values, which could have stemmed from over fitting, as captured by inflated errors amounts (RMSE, MSE, MAE). However, I found smaller error scores in the second experiment when outliers were excluded, which indicated better fit of the model to data. Hyperparameter tuning was done to further improve the performance of each model and Random Forest performed better than other models in the two experiments. For the Random Forest classifier its R-Squared scores were 83%, 82% along with 82.5% in consecutive assessments which make it quite reliable. This concurs with the study made by Joanna W. (2022) in which Random Forest outperformed neural networks and SVM algorithms in predicting Mars weather. The present work differed from the prior research done by Ishaani & Puri (2021), Ali M. (2021) and Alejandro (2019) which relied on pressure and temperature predictions using comparatively smaller datasets of REMS excluding EMIRS data but in this study, daily temperature fluctuations has been predicted using the dataset received from EMIRS. ANN and CNN models that were used in the Martian weather forecasting showed poor results on this dataset which indicates that the variability of datasets considerably influences the stability and efficiency of the models.

The study also confirmed the daily Martian temperature variation observed by Michael

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D. et al. (2022), as seen in the visualizations, supporting the findings of previous research.

Challenges, Conclusion, and Future Work Summary

5.1 Challenges:

Missing Values: The EMM EMIRS dataset had many missing values, which posed challenges during model development. Significant pre-processing was required, and assumptions were made that may have impacted the models' accuracy.

Time and Data Size: The large size of the dataset caused delays in importing the data and executing analyses. Hyperparameter fine-tuning for models took significant time, up to 30 minutes per model, due to the dataset's size.

5.2 Conclusion

This study achieved its objectives by exploring the diurnal variation in Martian atmospheric temperatures and examining the linear relationship among the four temperature types in the dataset. Preprocessing steps were conducted to prepare the data for model development. Two experiments were performed: the first with outliers present and the second with outliers removed. The second experiment, followed by hyperparameter tuning, resulted in better performance. Among the models, Random Forest outperformed others with RMSE=1.5525, MSE=2.4105, MAE=1.1939, and R^2=0.8283, demonstrating its suitability for Martian temperature prediction.

5.3 Future Work

Future research could explore other models, such as RNN, LSTM, and CCNN, which have been used for Mars weather prediction in the past. Additionally, future experiments should employ K-fold cross-validation for more reliable results. The dataset could also be expanded using newly released data from the EMM, which includes Martian weather data up to August 2022. Furthermore, more extensive hyperparameter tuning should be performed to optimize model performance, addressing the time and resource constraints faced in this study.

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