TITLE PAGE:

Predicting the Accuracy of Global Mean Temperature Using Linear regression compared with Adaboost

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**Keywords:** Linear regression, Adaboost,

# ABSTRACT

**Aim:** The purpose of this work is to improve the global mean Temperature . **Materials and Methods:** Linear regression and Adaboost is executed with varying training and testing splits for predicting the global mean Temperature . The Gpower test used is about 85% (g power setting parameters: α=0.05 and power=0.85). **Result:** Linear regression (88.7590%) has the increased accuracy over Adaboost (82.0500%) with a significance value of 0.009 (Two tailed, p>0.05). **Conclusion:** The accuracy of Linear regression is better when compared to accuracy of Adaboost.

Keywords: Linear regression, Adaboost,

# INTRODUCTION

We aim to use machine learning algorithms to model the mean temperature, namely Long-Short Term Memory Neural Networks (LSTM) and Random Forest Regressor (RF). For this study, we use a dataset with 30 years of radiosonde observations over the Brazilian region. In general, the results are consistent with those provided in the literature[(Brum et al. 2022)](https://paperpile.com/c/3AXnST/79pl),The proposed ensemble approach is based on three models which provide good performance in terms of model evaluation parameters like Correlation, Accuracy, R-Squared (R 2 ), Root mean square (RMSE) and Total Time to detect the predicted temperatures [(Himika et al. 2018)](https://paperpile.com/c/3AXnST/Ojlc).The purpose of this paper is to predict the most probable future global sea-level rise using advanced machine learning models. A total of 28 years' worth of sea-level rise data has been utilized for training our models using various machine learning algorithms[(Hassan et al. 2021)](https://paperpile.com/c/3AXnST/uFgL).Furthermore, the temporal and spatial variability in the modeled brightness temperatures via the SVM more closely agrees with that found in the original AMSR-E measurements. These findings suggest that the SVM is a superior alternative to the ANN for eventual use as a measurement operator within a data assimilation framework[(Forman and Reichle 2015)](https://paperpile.com/c/3AXnST/rhQq).

The research has been carried out onPredicting the accuracy of global mean Temperature using Machine learning; on an average of 44 research papers have been published in IEEE Xplore and 34 papers have been published in sciencedirect.The results were validated by in situ observations and compared with the NASA Advanced Microwave Scanning Radiometer for EOS (AMSR-E) snow water equivalent product. Satisfactory accuracy was achieved for different ecoregions with regard to daily, monthly, the Pearson correlation coefficient R ranged from 0.75 to 0.85)[(Xu et al. 2022)](https://paperpile.com/c/3AXnST/oZSx).

In this algorithm, the global precipitation measurement (GPM) product has been employed to train QPE prediction model. The real-time multiband infrared brightness temperature from Himawari-8, combined with the spatiotemporally matched numerical weather prediction (NWP) data from the global forecast system, have been used as predictor variables for QPE[(Min et al. 2019)](https://paperpile.com/c/3AXnST/e7jF). Considering that the sounding below the precipitation level becomes unreliable, the precipitation-affected observations were removed from the training dataset by means of a pre-screening test based on BT. The results show an overall ability of the algorithm to retrieve T and WV vertical profiles in line with expectations.[(Di Paola et al. 2018)](https://paperpile.com/c/3AXnST/SoBQ)

The research gap identified from the existing system is poor accuracy. This study is to improve

the accuracy of classification by incorporating Linear regression and comparing its performance with

Adaboost. The proposed model improves global mean Temperature

# MATERIALS AND METHODS

The research work was done in the Soft Computing Lab, Department, college name. Sample size has been calculated using Gpower software by comparing both the controllers. Two groups are selected for comparing the process and their result is derived. In each group, 10 sets of samples and 10 samples in total are selected for this work. Two algorithms Linear regression and Adaboost are implemented using technical Analysis software. Sample size is determined as 10 for each group using GPower 3.1 software (gpower setting parameters: α=0.05 and power=0.85).

The proposed work is designed and implemented with the help of Python OpenCV software. The platform to assess deep learning was Windows 10 OS. Hardware configuration was an Intel core i7 processor with a RAM size of 4GB. System sort used was 64-bit. For implementation of code, java programming language was used. As for code execution, the dataset is worked behind to perform an output process for accuracy.

**Linear regression**

**Description**

The machine learning algorithm Linear Regression is based on supervised learning. It does a task called regression. In regression, the independent variables are used to model a target prediction value. It is mostly used to figure out how different things relate to each other and make predictions.

**Pseudo code:**

Require: Training data D, number of epochs e, learning rate ŋ, standard deviation σ

Ensure: Weights ω0 , ω1,.....ωk

Initialise weights ω0 , ω1,.....ωk from standard normal distribution with

zero mean and standard deviation σ

for epoch in 1...e do

for each (x, y) **∈** D in random order do

**y ‘**←ω0 + Σki=1ωixi

if (**y ‘**>1 and y = 1) or (**y ‘**<-1 and y=-1) then continue

ω0← ω0 - η 2(**y ‘ -y)**

**For i in 1…..k do**

ωi← ωi - η 2(**y ‘ -y)**xi

end for

end for

return ω0 , ω1,.....ωk

**Adaboost**

**Algorithm:**

1. Assign equal weights to all the data points
2. Find the stump that does the best job classifying the new collection of samples by finding their Gini Index and selecting the one with the lowest Gini index
3. Calculate the “Amount of Say” and “Total error” to update the previous sample weights.
4. Normalize the new sample weights.

**Pseudocode:**

# Load data

iris = datasets.load\_iris()

X = iris.data

y = iris.target

# Split dataset into training set and test set

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.3) # 70% training and 30% test

# Create adaboost classifer object

abc = AdaBoostClassifier(n\_estimators=50, learning\_rate=1)

# Train Adaboost Classifer

model = abc.fit(X\_train, y\_train)

#Predict the response for test dataset

y\_pred = model.predict(X\_test)

# Model Accuracy, how often is the classifier correct?

print("Accuracy:",metrics.accuracy\_score(y\_test, y\_pred))

# Statistical Analysis

SPSS software is used for statistical analysis of Linear regression and Adaboost. Independent variables are image, objects, distance, frequency, modulation, amplitude, volume, decibels. Dependent variables are images and objects. Independent T test analysis is carried out to calculate accuracy for both methods.

# RESULTS

The proposed Linear regression and Adaboost were run at different times in Anaconda Navigator with a sample size of 10. Table 1 represents the predicted accuracy and loss of Linear regression.Table 2 represents the predicted accuracy and loss of Adaboost. These 10 data samples are used for each algorithm along with their loss values to calculate statistical values that can be used for comparison. From the results, it is observed that the mean accuracy of Linear regression was 88.7590% and Adaboost was 82.0500%. Table 3 represents mean accuracy values for Linear regression and Adaboost. Mean value of Linear regression is better when compared with the Adaboost with a standard deviation of 6.55630 and 3.13909 respectively. Table 4 shows the Independent sample T test data of Linear regression and Adaboost with the significance value obtained is 0.016 (Two tailed, p<0.05). Figure 1 denotes the comparison of Linear regression and Adaboost in terms of mean accuracy and loss.

Mean, standard deviation and standard error mean for Linear regression are 88.7590, 6.55630 and 2.07329 respectively. Similarly for Adaboost, the mean, standard deviation and standard error mean are 82.0500, 3.13909 and .99267 respectively. On the other hand, the loss values of Linear regression for mean, standard deviation and standard error mean are 11.2890, 6.47235 and 2.04674 respectively. For Adaboost, the loss values of Adaboost for mean, standard deviation and standard error mean are 17.9500, 3.13909 and .99267 respectively.

The group statistics value along with mean, standard deviation and standard error mean for the two algorithms are also specified. The graphical representation of comparative analysis, means of loss between two algorithms of Linear regression and Adaboost are classified. This indicates that Linear regression is significantly better with 88.7590% accuracy when compared with Adaboost classified accuracy of 82.0500%.

# DISCUSSION

In the given study, the significance value obtained is 0.009 (Two tailed, p>0.05) which implies that Linear regression appears to be better than Adaboost. Accuracy analysis of the Linear regression is analyzed as 88.7590% whereas the accuracy of Linear regression is 82.0500%.

This paper analyses and predicts the global land-ocean temperature index using time series analysis and python crawler technology to obtain data from NASA's official website for 137 years from 1880 to 2016. The data were first-order differenced and passed the significance test before ARIMA modelling. The model predicted 2022–2031 temperature indices more accurately.[(Hoerling and Kumar 2003)](https://paperpile.com/c/mMlxys/NTTo)The article discusses weather forecasting using linear regression. The maximum, minimum, and average temperature and dew point values from Nizhny Novgorod weather observations were used to create a test data set. A small set of data from the previous day may be enough to make accurate weather forecasts, according to studies. Forecast errors averaged 1.5 degrees.[(Olafsson and Bao 2020)](https://paperpile.com/c/mMlxys/l6H2)An efficient nonlinear weather prediction method is artificial neural network. This paper compares regression methods and nonlinear methods like artificial neural networks to compare temperature prediction performance.[(Jordanova et al. 2020)](https://paperpile.com/c/mMlxys/0aTI)Future Global Precipitation Measurement (GPM) satellite constellations will improve HRPP spatial and temporal resolutions. We used linear regression and an error propagation model to merge precipitation datasets to create a statistically better product than any single dataset or their average.[(Dodla 2022)](https://paperpile.com/c/mMlxys/cWSN)

The limitations of this study is that it takes a very long time to train Linear regression, especially with large datasets. The future scope of this study is that the system should be expanded to include a larger number of objects with lesser time consumption in training the data set.

# CONCLUSION

The accuracy value of the Linear regression is 88.7590% whereas the accuracy value of Adaboost is 82.0500%. Based on the analysis, Linear regression (88.7590%) performs better than Adaboost (82.0500%)

# DECLARATIONS

Conflicts of Interests

No conflict of interest in this manuscript.

# Authors Contribution

Author SA was involved in data collection, data analysis and manuscript writing. Author CPL was involved in conceptualization, data validation and critical reviews of manuscripts.

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# REFERENCES

G. Chen, B. Xiao, L. Wei, Z. Liao, J. Li and Z. Zhu, "Analysis of global land-based ocean temperature indices based on time series analysis," 2022 IEEE 6th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC ), 2022, pp. 679-683, doi: 10.1109/IAEAC54830.2022.9929784.

R. V. Sharapov, "Using Linear Regression for Weather Prediction," 2022 Wave Electronics and its Application in Information and Telecommunication Systems (WECONF), 2022, pp. 1-4, doi: 10.1109/WECONF55058.2022.9803493.

A. Sharaff and S. R. Roy, "Comparative Analysis of Temperature Prediction Using Regression Methods and Back Propagation Neural Network," 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI), 2018, pp. 739-742, doi: 10.1109/ICOEI.2018.8553803.

A. C. Turlapaty, N. H. Younan and V. Anantharaj, "Precipitation data merging using general linear regression," 2009 IEEE International Geoscience and Remote Sensing Symposium, 2009, pp. III-259-III-262, doi: 10.1109/IGARSS.2009.5417769.

N. Doshi, T. Turakhia, A. S. Nair, M. Pandya and R. Iyer, "Estimating Air Temperature using Land Surface Temperature products of INSAT-3D satellite," 2020 IEEE India Geoscience and Remote Sensing Symposium (InGARSS), 2020, pp. 177-180, doi: 10.1109/InGARSS48198.2020.9358919.

Z. Bian et al., "Retrieval of Leaf, Sunlit Soil, and Shaded Soil Component Temperatures Using Airborne Thermal Infrared Multiangle Observations," in IEEE Transactions on Geoscience and Remote Sensing, vol. 54, no. 8, pp. 4660-4671, Aug. 2016, doi: 10.1109/TGRS.2016.2547961.

Yunchang Cao, Feifei Zheng, Yifeng Xie and Yanmeng Bi, "Impact of the weighted mean temperature on the estimation of GPS precipitable water vapor," 2008 International Conference on Microwave and Millimeter Wave Technology, 2008, pp. 799-801, doi: 10.1109/ICMMT.2008.4540519.

Li Junyuan, Guo Jifeng and Xu Weixin, "Response of vegetation cover over Shaanxi province to global warming," 2011 International Symposium on Water Resource and Environmental Protection, 2011, pp. 2304-2306, doi: 10.1109/ISWREP.2011.5893727.

[D. Brum, V. F. Rofatto, L. Gonzaga, R. De Oliveira Pena, L. F. Sapucci and M. R. Veronez, "Mean Tropospheric Temperature Estimation Using Deep Learning and Ensemble Methods," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, 2022, pp. 6658-6661, doi: 10.1109/IGARSS46834.2022.9883387.](https://paperpile.com/c/3AXnST/79pl)

[Himika, S. Kaur and S. Randhawa, "Global Land Temperature Prediction by Machine Learning Combo Approach," 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 2018, pp. 1-8, doi: 10.1109/ICCCNT.2018.8494173.](https://paperpile.com/c/3AXnST/Ojlc)

[K. M. A. Hassan, M. A. Haque and S. Ahmed, "Comparative Study of Forecasting Global Mean Sea Level Rising using Machine Learning," 2021 International Conference on Electronics, Communications and Information Technology (ICECIT), 2021, pp. 1-4, doi: 10.1109/ICECIT54077.2021.9641339.](https://paperpile.com/c/3AXnST/uFgL)

[B. A. Forman and R. H. Reichle, "Using a Support Vector Machine and a Land Surface Model to Estimate Large-Scale Passive Microwave Brightness Temperatures Over Snow-Covered Land in North America," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8, no. 9, pp. 4431-4441, Sept. 2015, doi: 10.1109/JSTARS.2014.2325780.](https://paperpile.com/c/3AXnST/rhQq)

[X. Xu, X. Liu, X. Li, Q. Shi, Y. Chen and B. Ai, "Global Snow Depth Retrieval From Passive Microwave Brightness Temperature With Machine Learning Approach," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-17, 2022, Art no. 4302917, doi: 10.1109/TGRS.2021.3127202.](https://paperpile.com/c/3AXnST/oZSx)

[M. Min et al., "Estimating Summertime Precipitation from Himawari-8 and Global Forecast System Based on Machine Learning," in IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 5, pp. 2557-2570, May 2019, doi: 10.1109/TGRS.2018.2874950.](https://paperpile.com/c/3AXnST/e7jF)

[F. Di Paola et al., "Retrieval of Temperature and Water Vapor Vertical Profile from ATMS Measurements with Random Forests Technique," IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium, 2018, pp. 6014-6017, doi: 10.1109/IGARSS.2018.8518198.](https://paperpile.com/c/3AXnST/SoBQ)

**TABLES AND FIGURES**

**Table1.** Accuracy and Loss Analysis of Linear regression

| **Iterations** | **Accuracy(%)** | **Loss(%)** |
| --- | --- | --- |
| 1 | 88.4 | 11.6 |
| 2 | 89.7 | 10.3 |
| 3 | 90.8 | 9.2 |
| 4 | 91.01 | 8.99 |
| 5 | 92.1 | 7.9 |
| 6 | 91.8 | 8.2 |
| 7 | 93.6 | 6.4 |
| 8 | 94.8 | 5.2 |
| 9 | 95.4 | 4.6 |
| 10 | 96.06 | 3.94 |

**Table2.** Accuracy and Loss Analysis of Adaboost

| **Iterations** | **Accuracy(%)** | **Loss(%)** |
| --- | --- | --- |
| 1 | 77.3 | 22.7 |
| 2 | 78.4 | 21.6 |
| 3 | 79.6 | 20.4 |
| 4 | 80.7 | 19.3 |
| 5 | 81.5 | 18.5 |
| 6 | 82.1 | 17.9 |
| 7 | 83.9 | 16.1 |
| 8 | 84.7 | 15.3 |
| 9 | 85.6 | 14.4 |
| 10 | 86.7 | 13.3 |

**Table 3.** Group Statistical Analysis of Linear regression and Adaboost. Mean, Standard Deviation and Standard Error Mean are obtained for 10 samples. Linear regression has higher mean accuracy and lower mean loss when compared to Adaboost.

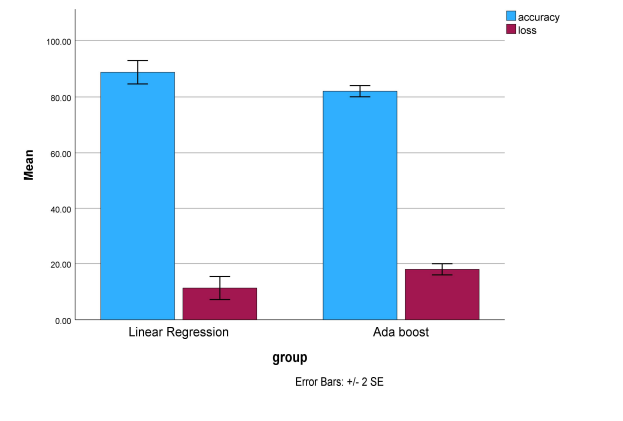
|  | **Group** | **N** | **Mean** | **Std. Deviation** | **Std. Error Mean** |
| --- | --- | --- | --- | --- | --- |
| **Accuracy** | Linear regression | 10 | 88.7590 | 6.55630 | 2.07329 |
| Adaboost | 10 | 82.0500 | 3.13909 | .99267 |
| **Loss** | Linear regression | 10 | 11.2890 | 6.47235 | 2.04674 |
| Adaboost | 10 | 17.9500 | 3.13909 | .99267 |

**Table 4.** Independent Sample T-test: Linear regression is insignificantly better than Adaboost with p value 0.009 (Two tailed, p<0.05)

|  | | **Levene’s test for equality of variances** | | **T-test for equality means with 95% confidence interval** | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **f** | **Sig.** | **t** | **df** | **Sig. (2-tailed)** | **Mean difference** | **Std.Error difference** | **Lower** | **Upper** |
| **Accuracy** | **Equal variances assumed** | 7.019 | 0.016 | 2.919 | 18 | 0.009 | 6.70900 | 2.29867 | 1.87967 | 11.53833 |
| **Equal Variances not assumed** | 2.919 | 12.920 | 0.009 | 6.70900 | 2.29867 | 1.73990 | 11.67810 |
| **Loss** | **Equal variances assumed** | 6.972 | 0.016 | -2.919 | 18 | 0.009 | -6.66100 | 2.27476 | -11.44008 | -1.88192 |
| **Equal Variances not assumed** | -2.919 | 13.012 | 0.009 | -6.66100 | 2.27476 | -11.57485 | -1.74715 |

**Table 5.** Comparison of the Linear regression and Adaboost with their accuracy

| **CLASSIFIER** | **ACCURACY(%)** |
| --- | --- |
| **Linear regression** | 88.7590 |
| **Adaboost** | 82.0500 |



**Fig 1.** Comparison of Linear regression and Adaboost. Classifier in terms of mean accuracy and loss. The mean accuracy of Linear regression is better than Adaboost. Classifier; Standard deviation of Linear regression is slightly better than Adaboost. X Axis: Linear regression Vs Adaboost Classifier and Y Axis: Mean accuracy of detection with +/-2SE.