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Research Article

Performance Analysis of Machine Learning Techniques for Predicting Sea Level Rise

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ABSTRACT

Climate science is a study of the earth's climate system, it was originated in the year nineteenth century, the purpose of climate science is to understand the weather patterns, ocean currents and the change climatic shifts. The field of climate changes it involves the contributions from a diverse range of professionals, including scientists, historians and sociologists. the efforts of the human to understand the natural forces which control the climate. In the recent research it was highlighted the impact of human activities like emission of gases etc. The ocean's surface is increased by the influence of melting glaciers and ice sheets, thermal expansion of sea water which in results are changing the global temperature and increasing in sea level which will be an increase in flood and erosion and mixture of salt water into fresh water resources. It is a multidisciplinary, highly international field in identifying the causes and potentially catastrophic consequences. by the early of nineties, the focus on anthropogenic climate change began to grow. Machine learning has been broadly adopted as the major tool for technological process. The ML, tools can be applied also for various climate change for monitoring natural forces. with the help of ML, we can identify the exact accuracy of any natural forces effecting earth's climate. It has an effective in climate model outputs and can have better quality in climate projections. The purpose of ML in climate change is to improve the understanding the climate change, prediction of climate through advance data driven techniques. By using ML into climate science, it helps to improve the accuracy and efficiency of climate models by detecting the climate changes and help in societal resilience. ML helps in reducing the uncertainties and helps to enhance the resolution of climate models. The outcomes of this paper state the climate change and attempts to describe the issues like Environmental, social, and economic viability. The impacts of climate change must be of the utmost importance, and hence, this global threat requires global commitment to address its dreadful implications to ensure global sustenance.

Keywords: Sea Level Rise, Machine Learning, Mean Squared Error, Mean Absolute Error, Random Forest and Decision Tree.

1. INTRODUCTION

Climate science is a multidisciplinary field dedicated to understanding the complex interactions within the Earth's climate system, including the atmosphere, oceans, land surfaces, and ice masses. In recent years, the significance of climate science has grown considerably due to the increasing severity of climate change impacts. Both natural processes and anthropogenic activities contribute to these changes, which have profound implications for ecosystems, human societies, and global economies [1]. One of the most direct effects of climate change is the increase in global temperatures. The average surface temperature of the Earth has risen by approximately 1.2°F to

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2.2°F due to the accumulation of greenhouse gases such as carbon dioxide (CO2) in the atmosphere. Recent years have been recorded as the hottest in history, correlating closely with industrial fossil fuel consumption. Additionally, the world's oceans absorb over 90% of the excess heat generated by greenhouse gases, leading to rising ocean temperatures, disruptions in marine ecosystems, and intensification of tropical storms [2]. Rising temperatures also influence atmospheric movement, altering jet streams and weather patterns, which in turn increase the frequency and intensity of extreme weather events such as droughts, storms, and heavy rainfall [3]. Warmer temperatures contribute to the formation of more powerful hurricanes and typhoons, as well as increased moisture retention in the atmosphere, which can lead to flooding during storms [4].

The primary objective of climate science is to study past, present, and future climate conditions. Through historical climate data analysis, paleoclimate studies, and advanced climate modeling, scientists seek to understand the mechanisms driving climate variability and change. This knowledge is crucial for predicting future climate scenarios and assessing their potential impacts on life on Earth [5]. Precipitation patterns play a significant role in the relationship between climate change and sea level rise. Increased rainfall, particularly in coastal and low-lying regions, can lead to severe flooding. Machine learning techniques, such as the Voting Regressor, enhance climate projections by integrating multiple models that capture various aspects of sea level changes and ocean dynamics, thereby improving predictive accuracy [6]. Other machine learning models, such as Random Forest and Support Vector Regression (SVR), are also instrumental in climate change predictions. Random Forest can analyze extensive datasets with multiple variables, including temperature, greenhouse gas emissions, wind speed, precipitation, and humidity, to improve forecasting accuracy for future sea levels and coastal management. Similarly, [7] SVR helps identify relationships between climate variables such as temperature, greenhouse gas concentration, and humidity, providing valuable insights into climate system dynamics, particularly in relation to ocean currents, atmospheric pressure systems, and ice system behavior [8].

Several evaluation metrics are used to assess the performance of machine learning models in climate science. The Mean Squared Error (MSE) measures the difference between predicted and actual values, with lower values indicating more accurate predictions. The Mean Absolute Error (MAE) evaluates the average differences between predicted and observed values, treating all errors equally. The R^2 Score quantifies the proportion of variance in observed data explained by the model, with values closer to one indicating a better fit [9].

MSE is a key metric for evaluating the performance of machine learning models in predicting climate change and sea level rise. It measures the difference between predicted and actual values, with lower values indicating predictions that are closer to observed data [10]. Conversely, higher MSE values suggest greater deviations from actual data. MAE, on the other hand, measures the average difference between predicted and observed values, providing a straightforward assessment of model accuracy. Unlike MSE, which penalizes larger errors more heavily, MAE treats all errors equally [11]. The R^2 Score is another important metric that quantifies the proportion of variance in observed data explained by the model. Values closer to one indicate a strong fit, capturing the underlying patterns and relationships between climate variables. The R^2 Score also plays a vital role in evaluating model generalization and improving long-term climate and sea level rise predictions [12].

Climate prediction involves the use of various models and datasets to forecast climate conditions on different time scales, from seasonal to long-term projections [13]. Computer simulations of the Earth's climate system incorporate key components such as the atmosphere, oceans, land, and ice surfaces. Models such as general circulation models (GCMs), Earth system models (ESMs), and regional climate models (RCMs) play a crucial role in predicting future climate changes and informing climate adaptation and mitigation strategies [14].

3. METHODOLOGY COMPARISON

Climate change is one of the biggest research domains where it requires an exact prediction about the seasoned climates. It does not occur permanently and keep on changing in the entire world. But this is can be predicted by having some excellent predetermined actions by taking so many parameters like, Temperature, Precipitation ratio, Humidity levels, Moisture, Noise, Water exist, solar radiation, Storms, Windiness, Fogginess, Sea Level Rise, Soil Erosion, Heavy rain falls and much more.

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3.1 Dataset Introduction

In this research, climate_change_dataset.csv is taken from [15] which includes the following attributes such as Date, Country, Location, Temperature, CO_2 Emissions, Precipitation, Humidity, Wind Speed and Sea Level Rise. Here, majorly Date, Country and Location is not being taken into consideration. Remaining parameters are adjudged to take the prediction of Sea Level Rise. This dataset includes 100001 records of the mentioned parameters. Actually, this dataset is modified a bit by changing all negative values into positive values for taking a better decision. This research discusses the comparison of various machine learning models for predicting the sea level rise to taken dataset (climate_change_dataset.csv) with respect to some parameters like R^2, Mean Square Error (MSE) and Mean Average Error (MAE). These metrics playing a very vital role in determining the accurate prediction and or deviating and all. Initially the heatmap analysis has been carried out which is depicted in the following Figure 1.

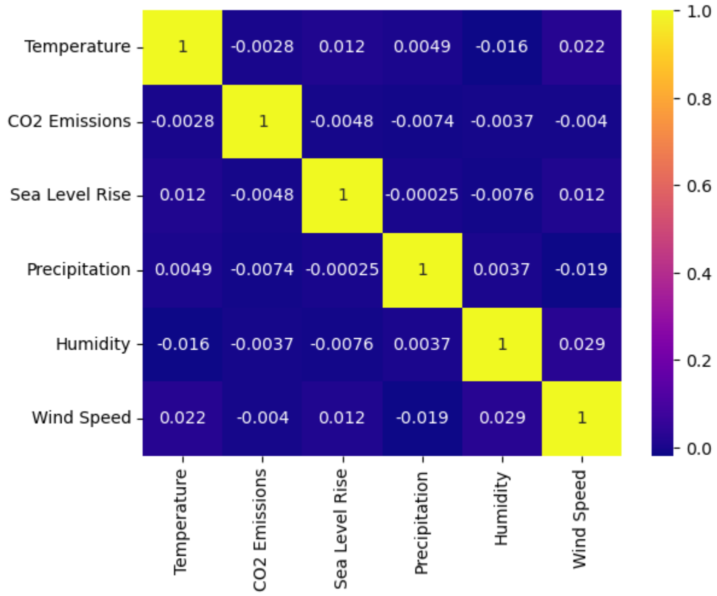

Figure 1. Heat Map Analysis of Parameters in the Climate Change Dataset

The following figure 2 explains the individual parameters comparison of machine learning techniques.

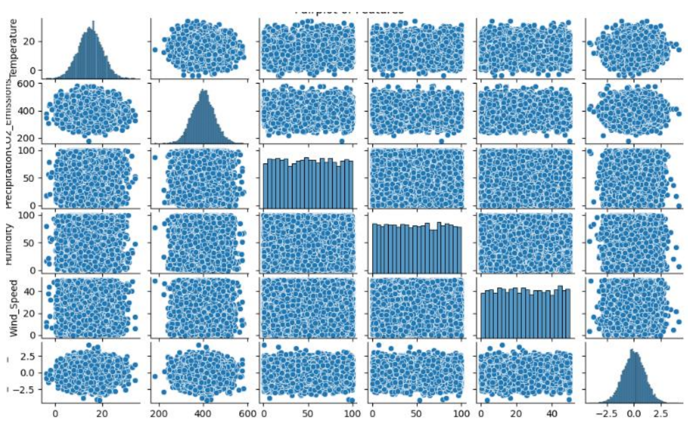

Figure 2 Machine Learning Individual Comparison

3.2 Parameters

To evaluate the performance of the comparison machine learning models the following metrics have been

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considered R2 Score, Mean Squared Error and Mean Average Error which is discussed below.

3.3 R^2 Score

In Regression based prediction, the R-squared (R^2) makes a big impact in determining the deviation of dependent variable values. It is a statistical scaling point which proves how well the particular machine learning model fits for the taken data. The formula is shown in the following figure 3.

$$R^2 = 1 - \frac{Sum\ Sqaured\ Regression\ (SSR)}{Total\ Sum\ of\ Squares\ (SST)}$$

Figure 3. The R^2 Formula

It represents the portion of the variation in the dependent variable that the model accounts for. R-squared ranges from 0 to 1, with higher values signifying that the model explains a greater amount of variability.

3.4 MSE

Mean Squared Error (MSE) is generally used to evaluate the regression performance with various datasets and its related models which is shown in Figure 4. It provides the average squared difference between the observed actual outcomes and the values which is predicted by the particular model. This value should be as minimum as possible, that is the Lowest MSE values indicate very good in its model performance.

$$\textbf{MSE} = \frac{1}{n}\sum_{y=1}^{n} (yi - \hat{y}i)^2$$

Figure 4. The MSE Formula

3.5 MAE

Mean Absolute Error (MAE) is a metric which is used for evaluating the various models performance of regressions. It gives the average magnitude of the errors in the all set of predictions, without observing their actual direction. Alike Mean Squared Error (MSE), which squares the errors, MAE looks the absolute value of the errors, also provides a more straightforward measure of its prediction accuracy. It is displayed in Figure 5.

$$\textbf{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\varkappa_i - x|^2$$

Figure 5. The MAE Formula

Scenario 1

The following result is taken by assuming 10 epochs with same configuration of the dataset with 70% training and 30% testing.

Table 1. Comparison of Regression Algorithms with 10 Epochs

S. No.	Model	R^2 Score	MSE	MAE
1	SVR	0.029381	0.996125	0.795132
2	Linear Regression	0.002510	0.970122	0.786526
3	KNN	0.212720	1.173541	0.863429
4	Decision Tree	1.160406	0.090612	0.158123
5	Random Forest	0.050538	1.016599	0.806176
6	AdaBoost	0.000170	0.967529	0.785036

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7	Voting	0.014131	0.981368	0.789923
8	MLP	0.022367	0.989339	0.792722

In the previous table, Decision Tree algorithm outperforms well by having the highest R^2 value, it shows variability in the dependent values (variables) and similarly, lowest value offered by the Adaboost model. Also, Decision Tree has lowest MSE value and KNN has the highest MSE as well. For MAE score, Decision Tree gives optimal result than others, plus KNN yields more.

Scenario 2

The following result is taken by assuming 20 epoch with same configuration of the dataset with 70% training and 30% testing which is presented in the Table 2.

Table 2. Comparison of Regression Algorithms with 20 Epochs

S. No.	Model	R^2 Score	MSE	MAE
1	SVR	0.034699	0.363738	0.462742
2	Linear Regression	0.001515	0.352073	0.472191
3	KNN	0.072295	0.376955	0.490623
4	Decision Tree	1.074325	0.381184	0.486597
5	Random Forest	0.010205	0.355128	0.473898
6	AdaBoost	0.406703	0.494513	0.601942
7	Voting	0.013764	0.356379	0.471182
8	MLP	0.024740	0.360237	0.473606

In the scenario 2 also, Decision Tree provides ultimate results in but for MSE score Linear Regression given least value than others. Regarding to MAE score Support Vector Machine gives least result than other algorithms.

Scenario 3

In the Table 3, result is taken by assuming 50 epoch with same configuration of the dataset with 70% training and 30% testing.

Table 3. Comparison of Regression Algorithms with 50 Epochs

S. No.	Model	R^2 Score	MSE	MAE
1	SVR	0.034699	0.363738	0.462742
2	Linear Regression	0.001515	0.352073	0.472191
3	KNN	0.072295	0.376955	0.490623
4	Decision Tree	0.681496	0.380189	0.486236
5	Random Forest	0.010736	0.355314	0.473517
6	AdaBoost	0.606569	0.564773	0.649421
7	Voting	0.016234	0.357247	0.471771

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8	MLP	0.031173	0.362499	0.473230

In the scenario 3, Decision Tree gives good results in R^2 score when looking with other algorithms, similarly, Linear Regression offers least results.

CONCLUSION

The study on the performance analysis of machine learning techniques for predicting sea level rise highlights the critical role of artificial intelligence in climate science. Climate change, driven by natural and anthropogenic factors, has led to rising global temperatures, extreme weather events, and increasing sea levels. The integration of machine learning models provides an advanced approach to predicting these changes with greater accuracy. Through comparative analysis, various machine learning algorithms, including Decision Tree, Random Forest, Support Vector Regression, and others, were evaluated based on their predictive performance using metrics like R^2 Score, Mean Squared Error (MSE), and Mean Absolute Error (MAE). The results indicate that the Decision Tree model consistently outperforms other algorithms by providing more accurate predictions with lower error rates. However, the effectiveness of models varies based on the number of epochs and dataset configurations. Machine learning significantly enhances climate projections by improving model precision, reducing uncertainties, and enabling data-driven decision-making for mitigating the adverse effects of climate change. Predicting sea level rise accurately is crucial for coastal management, disaster preparedness, and policy-making to prevent socio-economic and environmental damage. In conclusion, leveraging machine learning in climate science presents a promising avenue for enhancing climate predictions and improving resilience against climate-induced threats. However, further research is needed to refine models, integrate more diverse datasets, and address the challenges posed by complex climate dynamics. A collaborative global approach is essential to leveraging technology for climate adaptation and mitigation, ensuring sustainable solutions for future generations.

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