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Case Report

Utilizing time series data from 1961 to 2019 recorded around the world and machine learning to create a Global Temperature Change Prediction Model

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ABSTRACT

Since 1880, the Earth's temperature has increased at a pace of 0.14° Fahrenheit (0.08° Celsius) every decade; however, the rate of warming since 1981 is more than double that, at 0.32 °F (0.18 °C) per decade. Based on NOAA's temperature data, 2021 was the sixth hottest year on record. Warmer temperatures can also lead to a chain reaction of other global changes. That's because increasing air temperature affects the oceans, weather patterns, snow and ice, and plants and animals. The warmer it gets, the more severe the effects on people and the environment. The global average surface temperature has risen at an average rate of 0.17 °F per decade since 1901.

The Global Surface Temperature Change data recorded by the National Aeronautics and Space Administration Goddard Institute for Space Studies (NASA-GISS) was used in this paper.

This article attempted to design a model for Time Series Data from 1961 to 2020 for Global Temperature Change Prediction with the help of machine learning algorithms. Therefore, Extra Trees, light gradient boosting machine, Random Forest, K nearest neighbors, gradient boosting, and Bayesian ridge algorithms were investigated to create a Global Temperature Change Prediction Model and the evaluation criteria such as MAE (C°), MSE (C°), RMSE (C°), R2 and RMSLE (C °) and MAPE (C °) were calculated, and also the execution time of the algorithms was obtained in seconds. The obtained results showed that the Extra Trees algorithm has the best performance in predicting Global Temperature Change.

1. Introduction

Monitoring and forecasting temperature changes are essential to understand future climate trends better. Climate change is a contentious topic because of how negatively it affects people's lives [1]. According to projections, climate change will significantly affect river water quality in many parts of the world [5] or increase the probability of water-related catastrophes, including urban floods and severe droughts [2–4]. Understanding the future, especially in terms of temperature change, is crucial for assisting decision-makers in assessing and minimizing the consequences of climate change and improving infrastructure dependability [6–8]. It is well-recognized that temperature is essential when evaluating the level of human existence. A trustworthy and precise framework is required to effectively expect air temperature in the future [9]. Although making such forecasts with perfect precision may be unachievable, there are ways to reduce predicting mistakes or speed up showing [10,11]. New specialized methods have been introduced because of the current need for this knowledge, which has encouraged the development of new forecasting and data processing techniques [12–14]. These new tools, known as ML approaches, have shown their effectiveness over the last 2 Decades in various scientific and technical domains, including prediction issues [15–18]. LR, which may solve problems involving one or more variables, is one of the established and well-known Machine learning used in various environmental fields [19–21]. Regression issues are often solved using knn, a different nonparametric Machine learning approach [22–24]. Regression using SVM is another technique to identify relationships between inputs and outputs [24,25]. Last, the ANN is the best and most widely used approach, which detects nonlinear patterns in functional relationships, targets, and features. It has been used to solve a variety of Machine learning issues [26–28].

Deep Learning (DL) has become a promising method for time-series prediction problems like predicting the weather, and adaptive systems are better able to handle dynamic data [29]. In this study, researchers first examine the accuracy with which a DL based on LSTM can forecast climatic characteristics. The quality of the estimation method is then improved by using multiple LSTM types and selecting a method type that yields reliable and reliable results. The findings show that using just the

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multivariate method outcomes in learning from fewer characteristics, which saves time and memory when building and using the system.

In predicting air temperature at the Kordestan station in western Iran [30] for the next one, six, and twelve months, this issue suggests several novel stand-alone methods, such as the M5 prime and M5 rule along with hybridized methods utilizing the filtered classifier (FC). In order to do this, 3 decades' worth of data usage, spanning the years 1988–2018, were gathered, comprising information on absorption, peak, and lowest humidity levels rates, daylight hours, wind speed, and rainfall. Statistical criteria for simulation results showed that most created methods performed moderately to well, with M5 prime and M5 rule as well as their hybridized systems having the best forecasting accuracy.

The main goal of this work [31] is to examine the various ML approaches for temperature predicting that are described in the literature, outlining their benefits and drawbacks while also pointing out any unresolved issues. This study demonstrates how ML approaches may be used to forecast temperatures reliably using a variety of input characteristics, such as historical data on temperature, relative humidity, rainfall, and wind speed. In comparison to conventional ANN designs, DL techniques exhibit reduced mistakes (MSE = 0.0017 K) for 1 step-ahead at regional size.

In this research [32], artificial neural networks are used to forecast the average air temperature for smart agriculture. The findings show that artificial neural network models can be used to forecast temperatures in smart agriculture with fewer forecast errors than those attained with traditional approaches.

Especially when addressing climate change, ML algorithms for time series prediction are improving in accuracy and value. The distinction among them, therefore, becomes more and more crucial as even more ways are created. Leading Machine Learning techniques were used for a set of important climatology time series that served as the dependent variable in this study and a local temperature time series as the independent variable. The theory's overall efficacy in predicting the daily average temperature value [33] was assessed by comparing all the training and prediction outcomes. Every one of the Machine Learning techniques discussed was trained in real data before being used to forecast the temperature in the research region. The investigation showed that the ANN beat the other five evaluated techniques in both training and forecasting temperature values for the Memphis, Tennessee climate.

The purpose of this research [34] was to develop a hybrid approach for seasonal predicting of daily mean temperature increases at the field scale, which included coupling a global climate model. The results confirmed the hybrid algorithms' powerful ability to make long-range predictions at the field size. In particular, the hybrid model outperformed the climatology approach across all horizons to predictability (RMSE, 1.02–3.35).

In order to predict daily temperatures using just historical data and the weather service's highest and lowest forecasts, this research offers a hybrid forecasting system that blends linear methods [35].

The authors provide a novel approach [36] to short-term temperature prediction using a Radial Basis Functions Neural Network trained with data from a Regression Tree. In this article, the MAE evaluation criterion is 0.4466 °C appropriated.

In [37], the MLPNN method was used for Univariate Time Series Forecasting of Temperature and Precipitation and the RMSE value was 1.7 °C.

In [38], SVR and MLP methods were used for the monthly prediction of air temperature in Australia. The SVR algorithm obtained a value of 1.0073 °C in the MAE evaluation criterion, and the MLP algorithm had a weaker performance than SVR.

In this article, hyperparameters were tried to be adjusted (part 2) so that the proposed algorithms have the best performance in predicting Global Temperature Change in the shortest possible time. As a result, Extra Trees, light gradient boosting machine, Random Forest, K nearest neighbors, gradient boosting, and Bayesian ridge algorithms were investigated for Creating a Global Temperature Change Prediction Model and the evaluation criteria were MAE (C°), MSE (C°), RMSE (C°), R2, RMSLE (C°) and MAPE. (C°) and also the execution time of the algorithms was obtained in seconds. In part 2, the algorithms and the method of setting the hyperparameters of the algorithms were discussed, as well as the reason for using each algorithm in Create a Global Temperature Change Prediction Model, and then in part 3, the results of the suggestion algorithms (Extra Trees, light gradient boosting machine, Random Forest, nearest neighbors, gradient boosting, and Bayesian ridge) were investigated in the prediction of Global Temperature Change and finally, Comparison with other studies was made in section 4 the superiority of the proposed algorithms with other machine learning algorithms was shown and the conclusion was made in section 5.

2. Methods

According Fig. 1, the Temperature Change Prediction block diagram is shown. First, the Time Series Data from 1961 to 2019 Recorded Around the World, related to Temperature Change, is pre-processed. Outliers are removed (section 2.2), and data are normalized (section 2.1). Then the hyperparameters of the used algorithms (section 2.3) are set with grid search (section 2.4), and the results of hyperparameters for Extra Trees Regressor, Light Gradient Boosting Machine, Random Forest Regressor, K Neighbors Regressor, and Gradient Boosting Regressor Bayesian Ridge algorithms tuned by Grid Search CV are shown in Table 1.

2.1. Normalization data

Normalization is One common step in getting machine learning ready-to-use data. Normalization attempts to convert the numerical values of each column in a dataset to a standard scale without compromising the integrity of the data by flattening out ranges or erasing significant disparities. In this article, module Min-Max-Scaler () in python was used to normalize the data.

2.2. Standard Deviation

Outliers are data points significantly different from the rest of the values in a sample drawn from a larger population. An outlier is a data point that substantially deviates from the mean or median of a distribution or dataset a machine is supposed to learn from. Overfeeding occurs when an abnormality in the input data leads a machine-learning model to provide inaccurate predictions. Standard Deviation has a module as stdev() in Python. in this manuscript stdev() module was used.

2.3. Suggested research algorithms

2.3.1. Extra tree (ET)

This approach is extremely close to the RF algorithm, which is used to build several methods. There are two significant distinctions, however. The splitting of the descriptors at the node is entirely arbitrary, which is the first distinction. Instead of bootstrap sampling, every tree is constructed using the complete dataset as the second difference.

ET employs the same principles as the Random Forest (RF) method, training each base estimator with a random sample of topographies. The formed decision is represented by the nodes above the leaf node. RF and Artificial Neural Networks algorithms perform substantially worse than this strategy [39,40]. Therefore, the ET (Extra Tree) algorithm was used to create a Global Temperature Change Prediction Model to achieve the best performance.

2.3.2. Light gradient boosting machine

Deep learning has a more considerable temporal difficulty than the

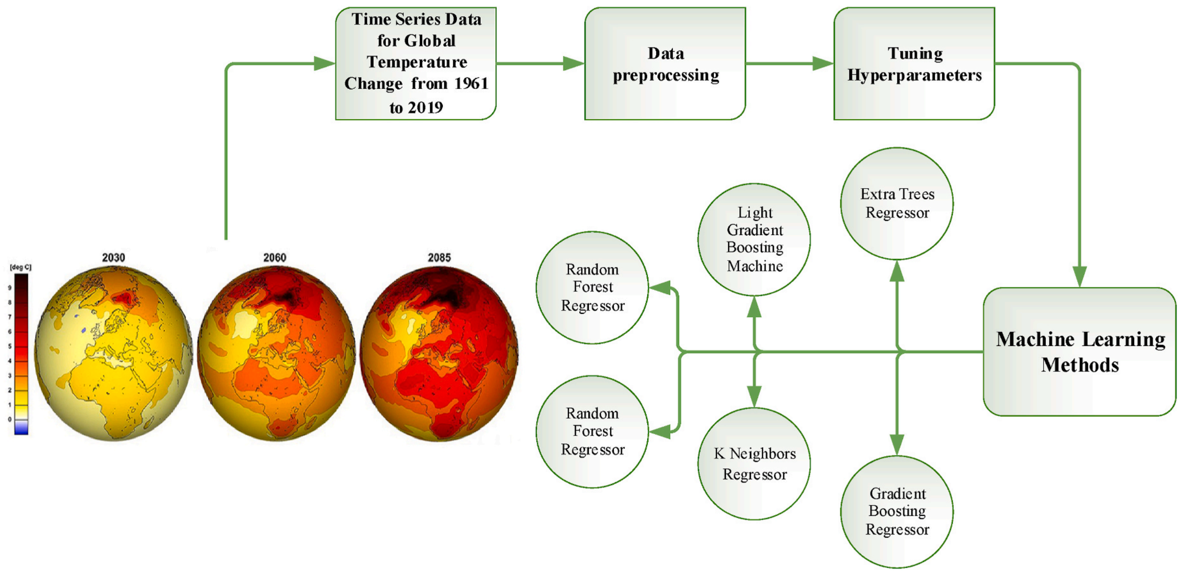

Fig. 1. Temperature Change Prediction block diagram.

Table 1
Hyperparameters.

Algorithm	Hyperparameters
knn	algorithm = auto leaf_size = 30 n_neighbors = 5 p = 2
Random forest	min_samples_leaf = 1 min_samples_split = 2 random_state = 3796
Bayesian Ridge	alpha_1 = 1e-06 alpha_2 = 1e-06 n_iter = 300
Gradient Boosting Regressor	alpha = 0.9 ccp_alpha = 0 max_depth = 3
Extra tree	min_samples_leaf = 1 min_samples_split = 2
Light gradient boosting machine	boosting_type = gbdt min_child_samples = 20 min_child_weight = 0.001

Light gradient boosting machine while capable of feature extraction and selection. When a new instance of the data stream is received, a deep learning network must update most of its parameters. In contrast, a new instance of streaming data requires the selection of critical features for the Light gradient boosting machine to learn further information; this causes fewer features, lowering the network's time complexity. As a result, before evaluating a new instance, the suggested model employs the Light gradient boosting machine to identify its essential properties. A Light gradient boosting machine does asynchronous computations on the historical streaming data and stores the outcomes. The outputs computed by the Light gradient boosting machine must be accessible when there is a new instance, which significantly saves processing time [40,41].

Due to the high accuracy and short execution time of the light gradient boosting machine algorithm [40,41], this algorithm was used to create a Global Temperature Change Prediction Model.

2.3.3. *Random forest*

ML tools called RF are often used for classification and regression problems. It is a set of independently created DT that were generated at random. In each tree, bootstrap sampling is the first kind of randomness introduced. The second kind of randomness refers to the subset chosen for each node's ideal split (n < N). It has been discovered that the random forest created with this two randomness is very reliable and accurate [42].

2.3.4. *k nearest neighbors*

KNN is a simple ML technique that may be used for various purposes. k nearest neighbors regression is a quick and easy method for any dataset [43]. Simply counting how many of our closest neighbors share our numerical goal will do the trick. This approach gives the most immediate neighbors the same weight regardless of their distance from the center. Identical distance functions to those used in the k nearest neighbors classification must determine sample dissimilarity for the regression. Both the Manhattan (ManDistance equation (2)) and the Euclidian (EucDistance equation (1)) distances are represented in this way. See how far apart the two locations of interest, x, and y, really are with the help of the equations below:

$$Euc_{Distance} = \sqrt{\sum_{i=1}^{k} (x_i - y_i)^2} \tag{1}$$

$$Man_{Distance} = \sum_{i=1}^{k} |x_i - y_i| \tag{2}$$

A given test instance (X,y) is compared to a training set D = [(Xi, yi)] for k Nearest neighbor learning. As an instance, the k Nearest neighbor calculates the distance di between each instance Xi in D and X and then organizes the distance di based on its value. The result is indicated as yi if di is rated *i*th, at which point the sample connected to di is known as the ith nearest neighbor (X). Regression's ultimate output, y, is shown in Eq. (3) to be the mean of its k nearest neighbors' outputs:

$$\hat{y} = \frac{1}{k} \sum_{i=1}^{k} y_i \ (X) \tag{3}$$

KNN is a simple ML technique that may be used for various purposes. K nearest neighbors regression is a quick and easy method for any dataset [43]. Therefore, it was used to create a Global Temperature Change Prediction Model.

2.3.5. *Gradient boosting*

The concept of an ensemble approach built from DTs (Decision Trees) is the foundation of gradient-boosting regression trees. A tree structure is used in the DT. The predicted outcome is the target leaf, which arises from the tree's root, branches by the circumstances, and moves toward the leaves. If the hierarchy is excessively deep, this decision tree has the drawback of over-fitting test data. DTs use the notion of the ensemble technique to avoid this over-fitting.

Gradient boosting Instead of using only one DT, this method combines many DTs. Standard techniques include gradient boosting and random forest. Splitting a dataset based on random numbers resulted in the creation of several decision trees in random forests. It avoids over-fitting by establishing predictions for each distinct decision tree and averaging the regression results [44]. Therefore, to avoid over-fitting, this method was used in Creating a Global Temperature Change Prediction Model.

A method known as gradient boosting involves constantly building decision trees such that each one corrects the inaccuracy of the preceding one. Outcomes are more sensitive to parameter adjustments during training compared to random forest. You will, however, receive more accurate test results with the correct parameter choices than with a random forest.

2.3.6. Bayesian ridge

Using probability distributions instead of point estimates when designing linear regression, Bayesian regression enables a natural process to survive the absence of adequate data or data with an uneven distribution [45], this method was used to create a Global Temperature Change Prediction Model. Instead of being estimated as a single value, the output or response "y" is believed to be chosen from a probability distribution.

2.4. Grid search CV

The data [46] included meteorological information for 190 countries and 37 other territorial entities from 1961 to 2019.70% of the data were considered training data, 15% as test data, and the remaining 15% as validation data. Simulations were done with the help of the 10-fold cross-validation [47–50] method and adjusting some hyperparameters of the used algorithms, which are shown in Table 1.

Grid Search CV is a strategy for finding the best parameter values in a grid, given a set of parameters. It is a cross-validation approach. Both the model and the parameters must be supplied. Predictions are created after obtaining the optimal parameter values.

Grid search 10-fold-cross-validation was used to choose the best model for each ML approach. Grid Search CV aids in obtaining a more accurate generalization performance estimate. 70% of the data were considered training data, 15% as test data, and the remaining 15% as validation data. Grid Search CV's aim is to reach the lowest prediction error. The prediction error formula is as follows:

$$CV(h) = \frac{1}{p}\sum_{j=1}^{p} T\left(y_j, h^{-l(j)}(xj)\right) \tag{4}$$

L: number of subsets
P: size of dataset
T: loss function (mean absolute error, mean squared error, root mean squared error, mean absolute percentage error, root mean squared logarithmic error)
$h^{-l(j)}(xj)$: the fitted function for each data point

Fig. 2 depicts the Grid Search CV approach used in this work for model training and hyperparameter selection.

3. Results and discussion

The Prediction Error chart in this article shows how robust an algorithm is in predicting Temperature Change. The actual temperature change value is displayed on the x-axis of this graph and the predicted temperature change value is displayed on the y-axis.

The prediction error chart can be analyzed as follows:

The prediction error diagram shows two lines of best fit and identity.

If the desired algorithm can predict all the values related to Temperature Change 100% and accurately, the two lines of best fit and identity will completely coincide and make an angle of 45° with the x-axis.

If the actual and predicted Temperature Change values differ from each other, the two lines of best fit and complete identity will not coincide and will not make a 45-degree angle with the X and Y axes.

Besides calculating the angle of the two lines of best fit and identity with the x and y axes, to show the strength of the algorithm used in predicting temperature change, the R2 evaluation criterion can also be used.

If the value of this evaluation criterion(R2) is closer to 1, It shows that the algorithm has been more successful in predicting Temperature Change.

The Residual plot in this article shows how strong an algorithm is in predicting Temperature Change. In this graph, the difference between the actual and predicted value of Temperature Change for training data and test data is displayed.

It shows the difference between the actual and predicted values of

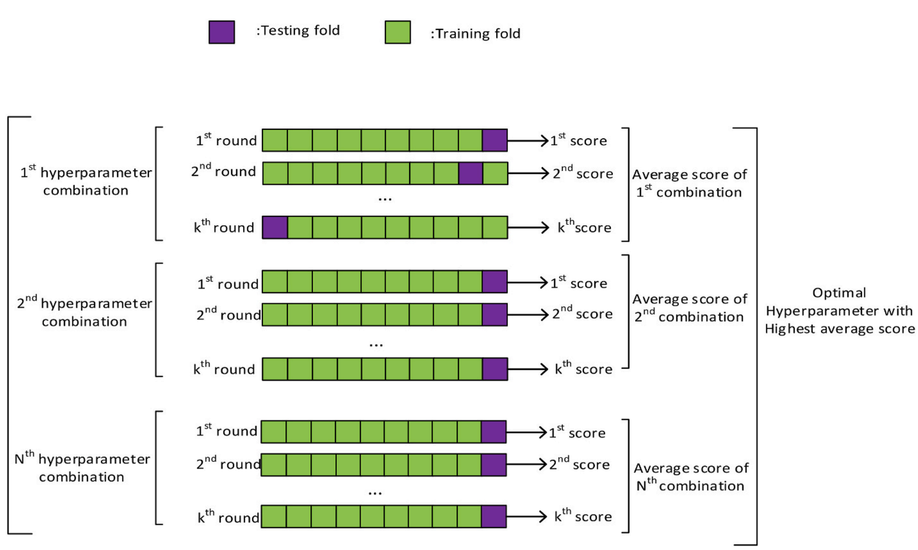

Fig. 2. Tuning hyperparameters.

Temperature Change for the training and test data as points. The blue points show the difference between the actual and predicted Temperature Change values for the training data, and the green points show the difference between the actual and predicted Temperature Change points for the test data.

The residual plot can be analyzed as follows:

If the actual value is greater than the predicted value, the point will be placed in the negative part of the Y-axis, and if the actual value is smaller than the predicted value, the point will be placed in the positive part of the Y-axis.

In Fig. 3, all the errors that Extra Trees, light gradient boosting machine, Random Forest, nearest neighbors, gradient boosting, and Bayesian ridge algorithms had on the test data in predicting Global Temperature Change are shown for shows two lines of best fit and identity. Also, in Fig. 4, all the errors that the Extra Trees, light gradient boosting machine, Random Forest, nearest neighbors, gradient boosting, and Bayesian ridge algorithms had on the test and training data in predicting Global Temperature Change are shown.

Fig. 3_a shows the Prediction Error for Forecasting Temperature Change with an extra tree. According to the form of evaluation criteria, the R2 value was 0.927. The R2 evaluation criterion shows the accuracy of algorithms in predicting regression problems. The value of 0.927 for the R2 evaluation criterion by this algorithm showed this algorithm could predict Temperature Change with an accuracy of 0.927.

Fig. 3_b shows the Prediction Error for Forecasting Temperature Change with a light gradient boosting machine. According to the form of evaluation criteria, the R2 value was 0.907. This algorithm performed weaker than the extra tree algorithm in predicting Temperature Change.

Fig. 3_c shows the Prediction Error for Forecasting Temperature Change with a random forest. According to the form of evaluation criteria, the R2 value was 0.894. This algorithm performed weaker than the light gradient boosting machine algorithm in predicting Temperature Change.

Fig. 3_d shows the Prediction Error for Forecasting Temperature Change with k nearest neighbors. According to the form of evaluation criteria, the R2 value was 0.822. This algorithm performed weaker than the random forest algorithm in predicting Temperature Change.

Fig. 3_e shows Prediction Error for Forecasting Temperature Change with gradient boosting. According to the form of evaluation criteria, the R2 value was 0.787. This algorithm performed weaker than the k nearest neighbors algorithm in predicting Temperature Change.

Fig. 3_f shows the Prediction Error for Forecasting Temperature Change with the Bayesian ridge. According to the form of evaluation criterion, the R2 value was 0.604. This algorithm performed weaker than the gradient boosting algorithm in predicting temperature change.

Fig. 4 compares the performance of the algorithms on the learning and training data and also shows in what interval the algorithms have the most errors on the training and test data.

A residual plot shows the difference between predicted and actual values. Fig. 4_a shows the residual plot for forecasting temperature change with an extra tree. According to the form of the R2 evaluation criterion for the training data, the accuracy was 0.935, so this algorithm has trained the training data with an accuracy of 0.935. Also, the R2 evaluation criterion for the test data was 0.927, so this algorithm can predict Temperature Change with an accuracy of 0.927. In Fig. 3_a, the R2 evaluation criterion for the test data was rated 0.927. In this figure, the R2 evaluation criterion, as in Fig. 3_a, was 0.927, which showed that the simulation was correct.

The distribution of the green points (the green points show the difference between the actual and predicted Temperature Change points for the test data) Fig. 4_a is between −1.5 C° and 3.5 C°, this shows that the interval The error of this model in Global Temperature Change

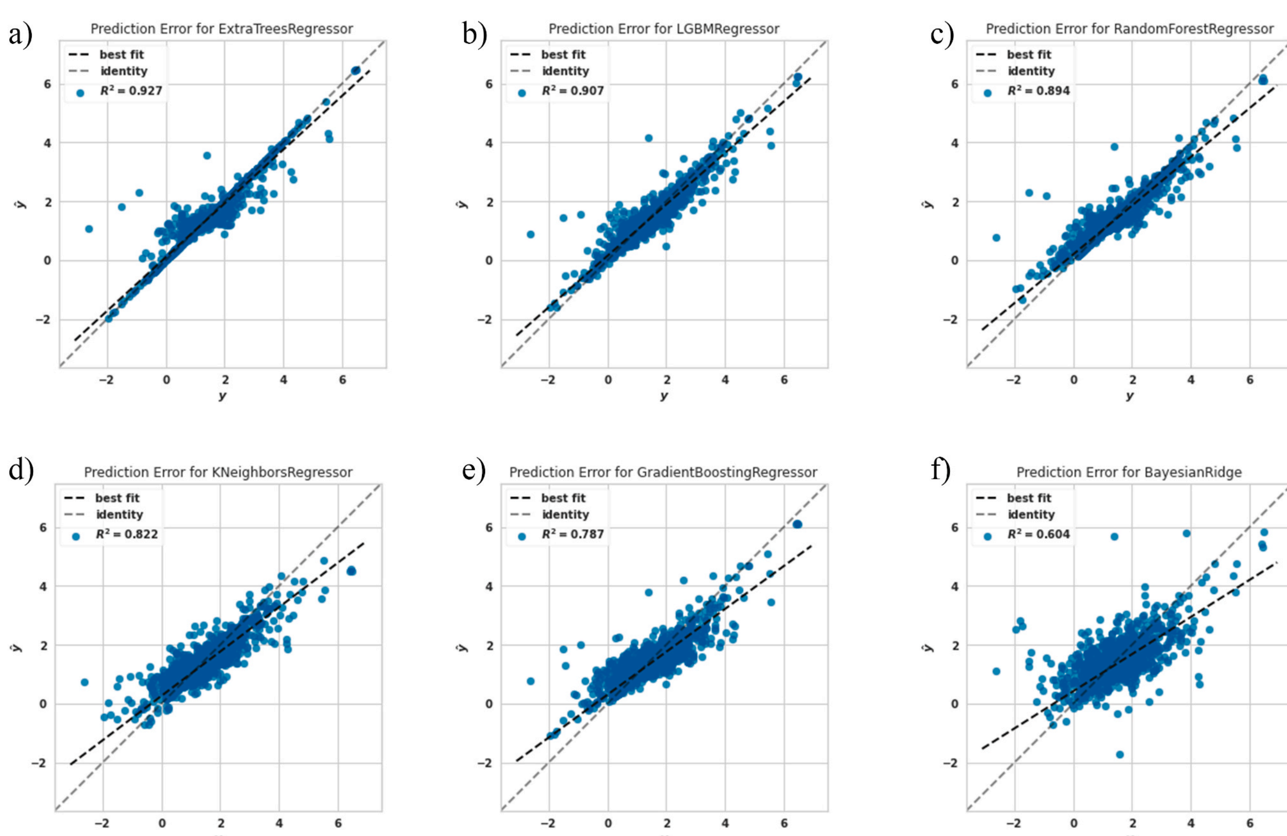

Fig. 3. Prediction Error for Forecasting Temperature Change with extra tree (a), light gradient boosting machine(b), random forest(c), k nearest neighbors(d), gradient boosting(e), Bayesian ridge(f).

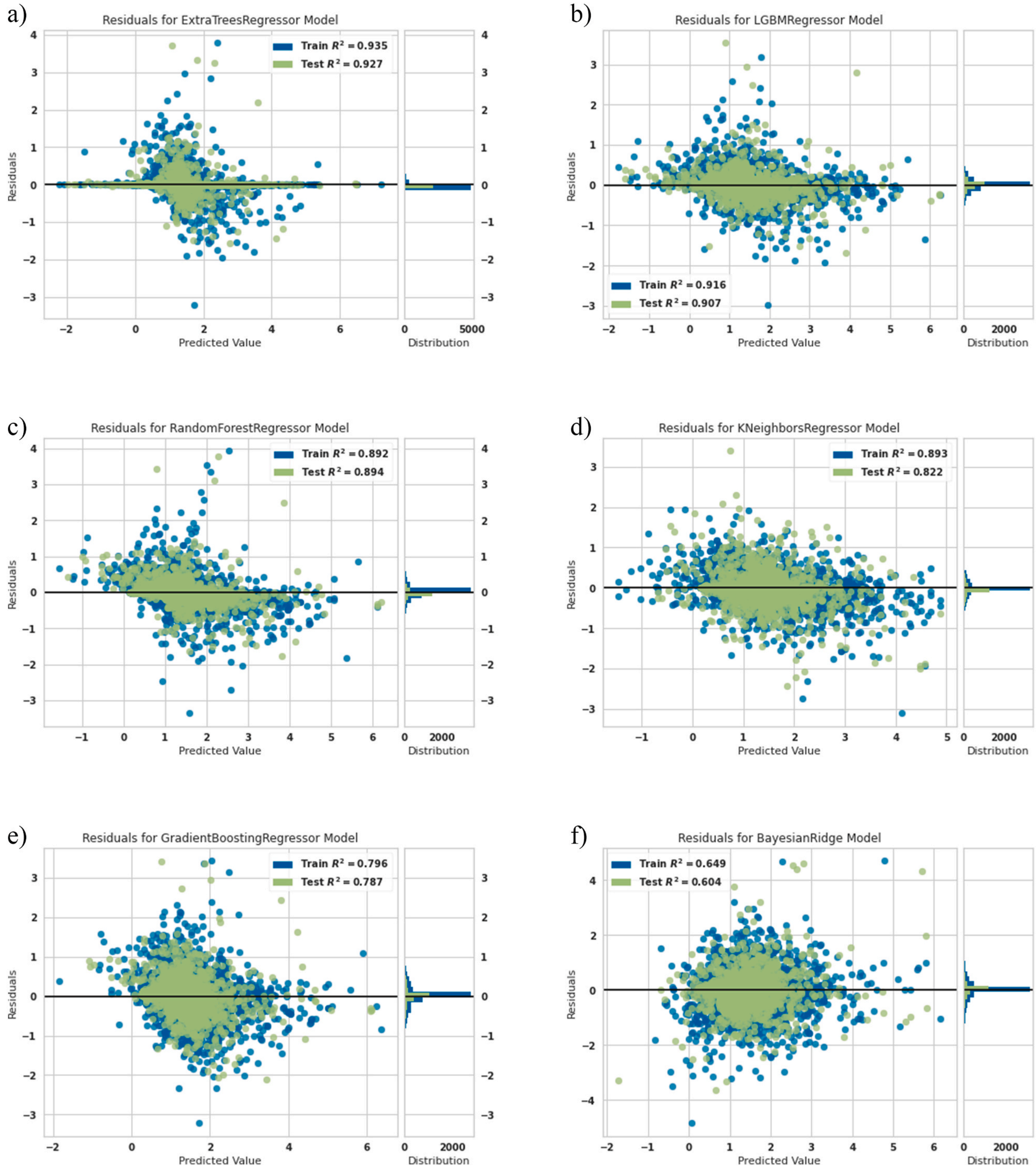

Fig. 4. Residual plot for Forecasting Temperature Change with extra tree (a), light gradient boosting machine(b), random forest(c), k nearest neighbors(d), gradient boosting(e), Bayesian ridge(f).

Prediction is between −1.5 C° and 3.5 C°, and fortunately, the most errors are between 1 C° and −1, which shows that this model has a very accurate performance in Global Temperature Change Prediction.

By checking the blue points (The blue points show the difference between the actual and predicted Temperature Change values for the training data), it is between −3.5 C° and 4 C°, which shows that this algorithm has been trained well. The number of green and blue points of this method is less compared to other methods, this shows that this method has less errors in training and test data compared to other methods.

Fig. 4_b shows the residual plot for forecasting temperature change with a light gradient boosting machine. According to the form of the R2 evaluation criteria for the training data, the accuracy was 0.916. This means that this algorithm has trained the training data with an accuracy of 0.916. Also, the R2 evaluation criterion for the test data was 0.920, so this algorithm can predict Temperature Change with an accuracy of 0.907. In Fig. 3_b, the R2 evaluation criterion for the test data was 0.907. In this figure, the R2 evaluation criterion, like Fig. 3_b, was 0.907, which showed that the simulation was correct.

The dispersion of the green points in Fig. 4_b is between −1.5 C° and

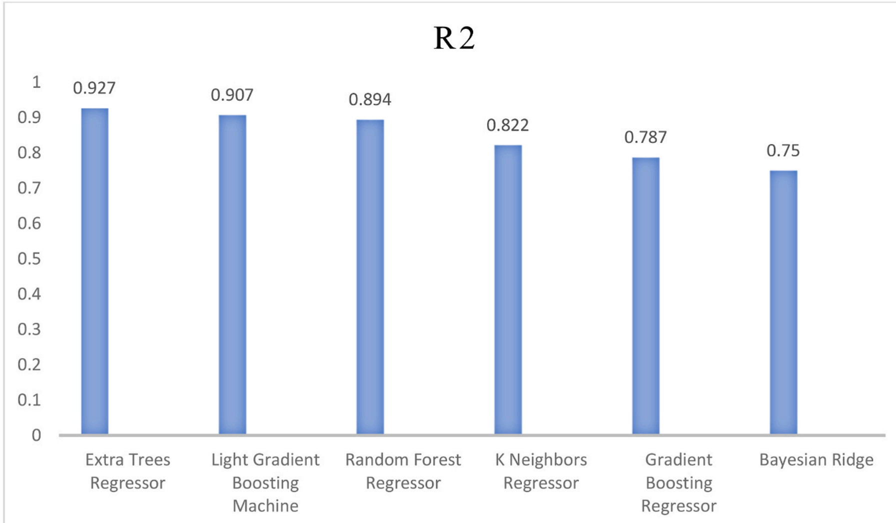

Fig. 5. Comparing the R2 evaluation criteria of the proposed suggested algorithms.

3.5 C°, this shows that the error range of this model in Global Temperature Change Prediction is between −1.5 C° and 3.5 C° Which shows that this model has a very accurate performance in Global Temperature Change Prediction. The blue points are between the numbers −3 °C and 3 °C, which shows that this algorithm is well trained.

Fig. 4_c shows the residual plot for forecasting temperature change with a random forest. According to the form of the R2 evaluation criteria for the training data, the accuracy was 0.892. Also, the R2 evaluation criterion for the test data was 0.894, so this algorithm can predict Temperature Change with an accuracy of 0.894. In Fig. 3_c, the R2 evaluation criterion for the test data was 0.894. In this figure, the R2 evaluation criterion, as in Fig. 3_c, was 0.894, which showed that the simulation was correct. The distribution of green points 4-c is between −2 C° and 3.9 C°, this shows that this model predicts Global Temperature Change with an error between −2 C° and 3.9 C°.

Fig. 4_d shows the Prediction Error for Forecasting Temperature Change with k nearest neighbors. According to the form of the R2 evaluation criteria for the training data, the accuracy was 0.893, which means that this algorithm was trained with the training data with an accuracy of 0.893. Also, the R2 evaluation criterion for the test data took the value of 0.822, which means that this algorithm can predict Temperature Change with an accuracy of 0.822. In Fig. 3_d, the R2 evaluation criterion for the test data was obtained as 0.822. In this figure, the R2 evaluation criterion, as in Fig. 3_d, got a value of 0.822, showing that the simulation was correct.

Fig. 4_e shows the residual plot for forecasting temperature change with gradient boosting regressor. According to the form of the R2 evaluation criterion for the training data, the accuracy was 0.796, which means that this algorithm has trained the training data with an accuracy of 0.796. Also, the R2 evaluation criterion for the test data was 0.787, which means that this algorithm can predict Temperature Change with an accuracy of 0.787. In Fig. 3_e, the R2 evaluation criterion for the test data was 0.822. In this figure, the R2 evaluation criterion, as in Fig. 3_e, was 0.787, showing that the simulation was correct.

Fig. 4_f shows the residual plot for forecasting temperature change with the Bayesian ridge. According to the form of the R2 evaluation criteria for the training data, the accuracy was 0.649, which means that this algorithm has trained the training data with an accuracy of 0.649. Also, the R2 evaluation criterion for the test data was 0.604, which means that this algorithm can predict Temperature Change with an accuracy of 0.604. In Fig. 3_f, the R2 evaluation criterion for the test data was 0.604. In this figure, the R2 evaluation criterion, as in Fig. 3_f, was 0.604, which showed that the simulation was correct.

The number of green and blue points in Fig. 4-a is much less compared to Fig. 4-b, 4-c, 4-d, 4-e and 4-f, this shows that the extra tree algorithm has a better performance in Global Temperature Change Prediction.

Comparing the R2 evaluation criteria of the proposed algorithms is shown in Fig. 5. The best performance among the proposed algorithms was related to the extra tree, and the worst was associated with the Bayesian ridge.

Fig. 6 shows the comparison of the execution time of the proposed algorithms. The lowest running time among the proposed algorithms was related to the Bayesian ridge, and the highest running time was associated with the random forest.

4. Comparison with other studies

In this paper Extra Trees Regressor, Light Gradient Boosting Machine, Random Forest Regressor, K Neighbors Regressor, Gradient Boosting Regressor, Bayesian Ridge algorithms are assigned as suggested methods.

The evaluation criteria Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), Root Mean Squared Logarithmic Error (RMSLE), Mean absolute percentage error (MAPE), coefficient of determination(R2) of the proposed algorithms Extra Trees Regressor, Light Gradient Boosting Machine, Random Forest Regressor, K Neighbors Regressor, Gradient Boosting Regressor Bayesian Ridge, and other machine learning algorithms are given in Table 2. Among the proposed algorithms, the best performance was related to the proposed Extra Trees Regressor algorithm, and the worst performance was related to the Bayesian Ridge algorithm. Comparing the performance of the proposed algorithms with other machine learning algorithms, the superiority of the proposed algorithms over different algorithms can be seen. I was trying to compare my results with other algorithms I simulated, and because of their weak results, I didn't suggest those algorithms as my suggested methods.

To compare the performance of the proposed algorithms with other methods of the articles, the following comparisons were made:

In this article [33], the evaluations revealed that, except for SVM, all the algorithms were adequately trained. R2 for SVM was just 0.5560, the lowest of any method. And the ANN method assigned the highest value of R2, which assigned the value of 0.9044 for R2. Meanwhile, our proposed Extra Trees Regressor method has reached R2 = 0.927.

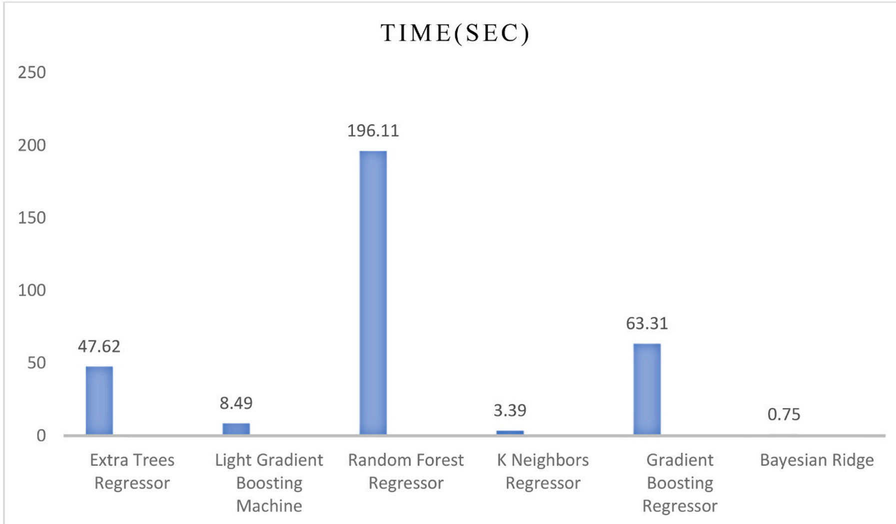

Fig. 6. Comparison of the execution time of proposed suggested algorithms.

Table 2
Evaluation criteria of proposed algorithms and other machine learning algorithms.

Mode1	MAE(C°)	MSE(C°)	RMSE(C°)	R2	RMSLE(C°)	MAPE(C°)	Time (Sec)
Extra Trees Regressor	0.1955	0.1610	0.3998	0.927	0.1480	0.4620%	47.62
Light Gradient Boosting Machine	0.2071	0.1642	0.4033	0.907	0.1527	0.41125%	8.49
Random Forest Regressor	0.2188	0.1948	0.4393	0.894	0.1611	0.5126%	196.11
K Neighbors Regressor	0.1896	0.1452	0.3802	0.822	0.1427	0.3664%	3.39
Gradient Boosting Regressor	0.2512	0.2174	0.4650	0.787	0.1749	0.5542%	63.31
Bayesian Ridge	0.2903	0.2816	0.5293	0.604	0.1973	0.6151%	0.75
Linear Regression	0.2900	0.2821	0.5298	0.6006	0.1976	0.6126%	3.56
Ridge Regression	0.2900	0.2821	0.5298	0.6005	0.1976	0.6127%	2.9
Least Angle Regression	0.2909	0.2876	0.5350	0.6	0.1987	0.6167%	0.60
Huber Regressor	0.2683	0.2913	0.5384	0.5999	0.1962	0.5695%	5.89
Orthogonal Matching Pursuit	0.3508	0.3502	0.5901	0.5295	0.2228	0.7286%	0.44
AdaBoost Regressor	0.4582	0.3717	0.6091	0.4967	0.2544	1.0317%	16.36
Decision Tree Regressor	0.3083	0.3997	0.6295	0.4619	0.2351	0.56515%	6.24
Passive Aggressive Regressor	0.3899	0.4847	0.6929	0.3458	0.2465	0.8055%	0.62
Lasso Regression	0.6512	0.7445	0.8615	−0.0014	0.3546	1.3096%	0.29
Elastic Net	0.6512	0.7445	0.8615	−0.0014	0.3546	1.3096%	0.27
Lasso Least Angle Regression	0.6512	0.7445	0.8615	−0.0014	0.3546	1.3096%	0.40
Dummy Regressor	0.6512	0.7445	0.8615	−0.0014	0.3546	1.3096%	0.24

The purpose of this research [34] was to develop a hybrid approach for seasonal predicting of daily mean temperature increases at the field scale, which included coupling a global climate model. The results confirmed the hybrid algorithms' powerful ability to make long-range predictions at the field size. In particular, the hybrid model outperformed the climatology approach across all horizons to predictability (RMSE, 1.02–3.35). Meanwhile, our proposed Extra Trees Regressor method has reached RMSE = 0.3998.

In order to predict daily temperatures using just historical data and the weather service's highest and lowest forecasts, this research offers a hybrid forecasting system that blends linear methods [35]. In this article, the evaluation criterion of MAPE was 2.66%. This was while the MAPE of the methods proposed in this article was between 0.4620% and 0.6151%.

The authors provide a novel approach [36] to short-term temperature prediction using a Radial Basis Functions Neural Network trained with data from a Regression Tree. In this article, the MAE evaluation criterion is 0.4466 °C appropriated. This was while the MAE of the methods proposed in this article was between 0.1955 and 0.2903.

In [37], the MLPNN method was used for Univariate Time Series Forecasting of Temperature and Precipitation and the RMSE value was 1.7 °C. Meanwhile, the proposed methods of this article had an RMSE between 0.3998 and 0.5293.

In [38], SVR and MLP methods were used for the monthly prediction of air temperature in Australia. The SVR algorithm obtained a value of 1.0073 °C in the MAE evaluation criterion, and the MLP algorithm had a weaker performance than SVR. Meanwhile, the proposed methods of this article assigned MAE between 0.1955 and 0.2903.

5. Conclusion

Droughts that are more frequent and extreme, storms, heat waves, rising sea levels, melting glaciers, and warmer seas may all directly injure animals, ruin the habitats they rely on for survival, and have a disastrous impact on people's way of life and communities. As climate change worsens, dangerous weather events become more frequent or severe. Even if we cannot halt global warming overnight, we can reduce human emissions of heat-trapping gases and soot (also known as "black carbon") to decrease the pace and restrict the quantity of global warming. In this article, to show the lousy situation of global warming, Time Series Data from 1961 to 2019 Recorded Around the World related to Global Temperature Change with the proposed algorithms Extra Trees Regressor, Light Gradient Boosting Machine, Random Forest Regressor, K Neighbors Regressor, Gradient Boosting Regressor Bayesian Ridge and other machine learning algorithms tried to design optimal models for predicting Global Temperature Change by adjusting the hyper-parameters of the algorithms and comparing the results of the proposed algorithms with other machine learning algorithms.

The results of the algorithms indicated that the Extra Trees algorithm reached RMSE = 0.3998 C° in 47.62 seconds, and the highest error of this algorithm in predicting Global Temperature Change was 3.5 °C. In comparing the performance of the proposed algorithms in the article, the Bayesian Ridge algorithm had the weakest performance so that the evaluation criterion of RMSE = 0.5293 C° was obtained, and also the highest error of the algorithm in predicting Global Temperature Change was about 5 °C.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cscee.2023.100312.

References

[1] S. Thober, R. Kumar, N. Wanders, A. Marx, M. Pan, O. Rakovec, L. Samaniego, J. Sheffield, E.F. Wood, M. Zink, Multi-model ensemble projections of European river floods and high flows at 1.5, 2, and 3 degrees global warming, Environ, Res. Lett 13 (2018), 014003.

[2] K. Mohammed, A.K.M.S. Islam, G.M.T. Islam, L. Alfieri, M.J.U. Khan, S.K. Bala, M. K. Das, Future floods in Bangladesh under 1.5°C, 2°C, and 4°C global warming scenarios, J. Hydrol. Eng. 23 (2018), 04018050.

[3] B. Azari, M. Tabesh, Urban storm water drainage system optimization using a sustainability index and LID/BMPs, Sustain. Cities Soc. 76 (2022), 103500.

[4] K. Azizi, C.I. Meier, Improving the Characterization of Urban Flash Floods through Application of Local Knowledge, in AGU Fall Meeting Abstracts 2020 (2020). H162–H160011.

[5] S. Ebrahimi, M. Khorram, Variability effect of hydrological regime on river quality pattern and its uncertainties: case study of Zarjoob River in Iran, J. Hydroinf. 23 (2021) 1146–1164.

[6] M. Tabesh, B. Azari, H. Rezaei, in: Hydraulic Performance Assessment of Stormwater Networks, in Proceedings of the International Conference on Civil, Architecture and Disaster Management (ICCADM-16), 2016, pp. 17–18. Hong Kong.

[7] B. Azari, M. Tabesh, Storm water drainage networks hydraulic performance assessment, international conference on sustainable development and urban construction, Iran 5 (2015) 10–16.

[8] K. Azizi, C.I. Meier, Urban Pluvial Flood Risk Assessment: Challenges and Opportunities for Improvement Using a Community-Based Approach, in World Environmental and Water Resources Congress 2021, 2021, pp. 350–361, https://doi.org/10.1061/9780784483466.033.

[9] D. Absalon, B. Ślesak, Air temperature increase and quality of life in an anthropogenically transformed environment: a case study, Polish J, Environ. Stud. 21 (2012) 235–239.

[10] Q. Song, B.S. Chissom, Forecasting enrollments with fuzzy time series — Part I, Fuzzy Set Syst. 54 (1993) 1–9.

[11] S.-M. Chen, J.-R. Hwang, Temperature prediction using fuzzy time series, IEEE Trans. Syst. Man, Cybern. Part B 30 (2000) 263–275.

[12] N. Zhong, S.S. Yau, J. Ma, S. Shimojo, M. Just, B. Hu, G. Wang, K. Oiwa, Y. Anzai, Brain informatics-based big data and the wisdom web of things, IEEE intell, Off. Syst. 30 (2015) 2–7.

[13] Z. Su, Q. Xu, Q. Qi, Big data in mobile social networks: a QoEoriented framework, IEEE Netw 30 (2016) 52–57.

[14] J. Wen, J. Yang, B. Jiang, H. Song, H. Wang, Big data driven marine environment information forecasting: a time series prediction network,, IEEE Trans. Fuzzy Syst. 29 (2021) 4–18.

[15] M. Alizamir, O. Kisi, A.N. Ahmed, C. Mert, C.M. Fai, S. Kim, N.W. Kim, A. El-Shafie, Advanced machine learning model for better prediction accuracy of soil temperature at different depths, PLoS One 15 (2020) 1–25.

[16] B. Azari, M. Tabesh, Optimal design of stormwater collection networks considering hydraulic performance and BMPs, Int. J. Environ. Res. 12 (2018) 585–596.

[17] A. Rahman, A. Khan, A.A. Raza, Parkinson's disease detection based on signal processing algorithms and machine learning, CRPASE Trans. Electr. Electron. Comput. Eng 6 (2020) 141–145.

[18] S.R. Moosavia, D.A. Woodb, S.A. Samadanic, Modeling Performance of Foam-CO2 Reservoir Flooding with Hybrid Machine-Learning Models Combining a Radial Basis Function and Evolutionary Algorithms, Methods 4, 2020, p. 5.

[19] K.A. Marill, Advanced statistics: linear regression, Part II: multiple linear regression, Acad. Emerg. Med. 11 (2004) 94–102.

[20] M.M. Ahmadi, H. Shahriari, Y. Samimi, A novel robust control chart for monitoring multiple linear profiles in phase II, Commun. Stat. Simulat. Comput. (2020) 1–12.

[21] S. Mehri, M.M. Ahmadi, H. Shahriari, A. Aghaie, Robust process capability indices for multiple linear profiles, Qual. Reliab. Eng. Int. 37 (2021) 3568–3579.

[22] J. Liang, Q. Yang, T. Sun, J.D. Martin, H. Sun, L. Li, MIKE 11 model-based water quality model as a tool for the evaluation of water quality management plans, J. Water Supply Res. Technol 64 (2015) 708–718.

[23] I. Saini, D. Singh, A. Khosla, QRS detection using K-Nearest Neighbor algorithm (KNN) and evaluation on standard ECG databases, J. Adv. Res. 4 (2013) 331–344.

[24] X. Wang, L. Ma, X. Wang, Apply semi-supervised support vector regression for remote sensing water quality retrieving, in: 2010 IEEE International Geoscience and Remote Sensing Symposium, 2010, pp. 2757–2760, https://doi.org/10.1109/IGARSS.2010.5653832.

[25] S. Liu, H. Tai, Q. Ding, D. Li, L. Xu, Y. Wei, A hybrid approach of support vector regression with genetic algorithm optimization for aquaculture water quality prediction,, Math. Comput. Model. 58 (2013) 458–465.

[26] A. Najah, A. El-Shafie, O.A. Karim, A.H. El-Shafie, Application of artificial neural networks for water quality prediction, Neural Comput. Appl. 22 (2013) 187–201.

[27] K.P. Singh, A. Basant, A. Malik, G. Jain, Artificial neural network modeling of the river water quality—a case study, Ecol. Model. 220 (2009) 888–895.

[28] B. Fotovvati, M. Balasubramanian, E. Asadi, Modeling and optimization approaches of laser-based powder-bed fusion process for Ti-6Al-4V alloy, Coatings 10 (2020).

[29] N. Abdulla, M. Demirci, S. Ozdemir, Design and evaluation of adaptive deep learning models for weather forecasting, Eng. Appl. Artif. Intell. 116 (2022) 105440. Nov 1.

[30] M. Shahdad, B. Saber, Multistep-ahead forecasting for maximum and minimum air temperatures using a new hybrid intelligence tree-based filter classifier, Modeling Earth Systems and Environment 8 (4) (2022) 5449–5465. Nov.

[31] J. Cifuentes, G. Marulanda, A. Bello, J. Reneses, Air temperature forecasting using machine learning techniques: a review, Energies 13 (16) (2020) 4215. Aug 14.

[32] F.J. Diez, A. Correa-Guimaraes, L. Chico-Santamarta, A. Martínez-Rodríguez, D. A. Murcia-Velasco, R. Andara, L.M. Navas-Gracia, Prediction of daily ambient temperature and its hourly estimation using artificial neural networks in an agrometeorological station in Castile and León, Spain. Sensors 22 (13) (2022 Jun 27) 4850.

[33] B. Azari, K. Hassan, J. Pierce, S. Ebrahimi, Evaluation of machine learning methods application in temperature prediction, Environ. Eng. 8 (2022) 1–2.

[34] J.Y. Shin, K.R. Kim, J.C. Ha, Seasonal forecasting of daily mean air temperatures using a coupled global climate model and machine learning algorithm for field-scale agricultural management, Agric. For. Meteorol. 281 (2020 Feb 15) 107858.

[35] H.S. Hippert, C.E. Pedreira, R.C. Souza, Combining neural networks and ARIMA models for hourly temperature forecast. In proceedings of the IEEE-INNS-ENNS international joint conference on neural networks, IJCNN 2000, neural computing: new challenges and perspectives for the new millennium, como, Italy 27 (July 2000).

[36] P.A.G. Lanza, J.M.Z. Cosme, A short-term temperature forecaster based on a novel radial basis functions neural network, Int. J. Neural Syst. 11 (2001) 71–77.

[37] G. Papacharalampous, H. Tyralis, D. Koutsoyiannis, Univariate time series forecasting of temperature and precipitation with a focus on machine learning algorithms: a multiple-case study from Greece. Water resour, OR Manag. 32 (2018) 5207–5239.

[38] S. Salcedo-Sanz, R.C. Deo, L. Carro-Calvo, B. Saavedra-Moreno, Monthly prediction of air temperature in Australia and New Zealand with machine learning algorithms, Theor. Appl. Climatol. 125 (2015) 13–25.

[39] S.M. Malakouti, A.R. Ghiasi, A.A. Ghavifekr, P. Emami, Predicting wind power generation using machine learning and CNN-LSTM approaches, Wind Eng. 46 (6) (2022 Dec) 1853–1869.

[40] G. Ke, et al., Lightgbm: a highly efficient gradient boosting decision tree,, Adv. Neural Inf. Process. Syst. 30 (2017) 3146–3154.

[41] M. Tang, et al., An improved lightGBM algorithm for online fault detection of wind turbine gearboxes," Energies, vol, 13, no 4 (2020) 807.

[42] S.M. Malakouti, Use machine learning algorithms to predict turbine power generation to replace renewable energy with fossil fuels, Energy Explor. Exploit. (2022 Nov 14), 01445987221138135.

[43] O. Kramer, O. Kramer, K-nearest neighbors, Dimensionality reduction with unsupervised nearest neighbors (2013) 13–23.

[44] J.H. Friedman, Stochastic gradient boosting, Comput. Stat. Data Anal. 38 (4) (2002 Feb 28) 367–378.

[45] H. Michimae, T. Emura, Bayesian ridge estimators based on copula-based joint prior distributions for regression coefficients, Comput. Stat. 37 (5) (2022 Nov) 2741–2769.

[46] https://www.kaggle.com/datasets/sevgisarac/temperature-change.

[47] S.M. Malakouti, A.R. Ghiasi, Evaluation of the application of computational model machine learning methods to simulate wind speed in predicting the production capacity of the Swiss basel wind farm, in: 2022 26th International Electrical Power Distribution Conference (EPDC), IEEE, 2022 May 11, pp. 31–36.

[48] S.M. Malakouti, A.R. Ghiasi, A.A. Ghavifekr, AERO2022-flying danger reduction for quadcopters by using machine learning to estimate current, voltage, and flight area. e-Prime-Advances in Electrical Engineering, Electronics and Energy 2 (2022 Jan 1) 100084.
[49] S.M. Malakouti, Using machine learning to diagnose benign and malignant breast tissues with the best degree of accuracy and in the shortest amount of time, Chemo open access 10 (166) (2022), https://doi.org/10.35248/2167–7700.22.10.166, 02-Dec-2022.
[50] S.M. Malakouti, Prostate cancer recognition: using the random forest technique and other ml techniques, Chemother. Open Access 10 (170) (2022), https://doi.org/10.35248/2167-7700.22.10.170, 06–Dec-2022.