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Estimating Tidal Sea levels along the Central Coast of the Western Arabian Gulf using Machine Learning Algorithms (MLAs)

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Abstract: ***Precise tidal forecasting is an academic exercise and a crucial tool for designing and constructing coastal and marine infrastructure. Machine learning algorithms (MLAs) like Random Forest Regression (RF), K-Nearest Neighbors Regression (KN), Gradient Boosting Machines (GBM), and artificial neural networks (ANNs) are powerful data-driven techniques that can be harnessed for this practical purpose. This study utilizes four machine learning algorithms (MLAs), namely (RF), (KN), (GBM), and the Artificial Neural Network - Multilayer Perceptron (ANN-MLP) model, to accurately estimate the tidal levels along the central coast of the western Arabian Gulf, with direct implications for real-world infrastructure planning and construction. Several metrics, such as mean absolute error (MAE), mean squared error (MSE), normalized mean square error (NMSE), mean absolute percentage error (MAPE), correlation coefficient (R), and root mean square error (RMSE), are used to compare how well the MLAs forecast daily tidal levels. The results confirmed the ANN-MLP model's superiority over the other approaches. The ANN-MLP model, a specific type of artificial neural network, yields enhancements in (RMSE) of 8.945% and 19.05%, 14.18% compared to (RF), (KN), and (GBM), respectively, throughout the testing process. The ANN-MLP, being a powerful and versatile machine learning algorithm, demonstrated the best level of accuracy, together with the lowest values for (RMSE). This experiment unequivocally proves that the ANN-MLP method can be utilized as a supervised machine-learning method for accurately forecasting seawater levels of tidal.***

Keywords: The Arabian Gulf, Machine Learning Algorithms, Tidal Level, Forecasting.

I. INTRODUCTION

Tides arise from the gravitational influences produced by the moon and sun on distinct regions of the rotating Earth, causing periodic water motion [1]. Accurately forecasting tides is crucial for effectively utilizing and harnessing marine resources, particularly in mitigating and minimizing maritime disasters. Precise forecasting of tidal levels is a critical concern for planning coastal and offshore structures and coastal development [2]. Previous studies have conducted various models for predicting tidal levels [1,2].

Soft computing techniques, such as machine learning algorithms (MLAs), have recently gained popularity for analyzing and predicting sea-level data. This is due to their advantages, such as adaptivity, nonlinearity, processing mechanism, and arbitrary approximation [3] [14] [15] [16] [17] [18]. Vaziri [4] conducted a comparison between multiplicative autoregressive integrated moving average (ARIMA) modeling and (ANNs) to assess their respective abilities. Liu, Shi, and Zhu [5] employed a machine-learning method to forecast tides. They discovered that the cascade correlation technique exhibited the shortest training time and was well-suited for adaptive training objectives. Lee and Tsai [6] utilized a gradient descent technique beside the Back Propagation Neural Network to forecast shoreline tide levels of Mirtuor. However, their model is limited to making instantaneous predictions, namely at the most recent prediction. Steidley, Tissot, Sadovski, Bowles, and Bachnak [8] employed an Artificial Neural Network (ANN) to enhance the accuracy of sea level predictions in cases where the performance of tide charts is abysmal. Machine learning algorithms (MLAs) like (ANNs) [7], (RF), (KN), and (GBM) are effective data-driven techniques that are not commonly employed for predicting tidal level prospectivity. Consequently, a comprehensive comparative evaluation of these methods in this field needs to be improved. Over the past few decades, numerous classification systems have been devised. Decision trees (DTs) [8] are frequently used approaches. Artificial neural networks (ANNs) support vector machines (SVMs) [8] and ensembles of classification trees like random forest (RF). This work meticulously assesses the precision of an MLA methodology by employing various algorithms (RF, KN, GBM, and ANN-MLP models) to predict daily tidal levels. A genetic algorithm (GA) is used to identify the appropriate structure of the machine learning algorithm (MLA) and the best parameter values for each MLA method. The performances of several MLAs are compared in terms of their ability to predict daily tidal levels prospectivity, instilling confidence in the thoroughness of the research. The assessment criteria utilized for comparison include (MAE), (MSE), (NMSE), (MAPE), (R), and (RMSE).

II. STUDY AREA

The Arabian Gulf is a body of water in West Asia, resembling the Gulf of Mexico.

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The body of water stretches across the Indian Ocean between Iran and the Arabian Peninsula. The Strait of Hormuz connects it to the Gulf of Oman in the east. The Shatt al-Arab River delta constitutes the shoreline in the northwest direction. The coastline is 989 kilometers (615 miles), with Saudi Arabia occupying most of the western coast of the Arabian Gulf. The Arabian Gulf's width narrows to around sixty-five kilometers (35 miles) at its narrowest point, located near the Strait of Hormuz. In general, the waters are shallow, reaching a maximum depth of 90 meters (295 feet) and an average depth of 50 meters (164 feet) [9]. The Ras Tanura complex is situated south of the contemporary industrial port city of Jubail, which was previously a fishing village. It is also positioned to the north of Tarut Bay, across from the old port city of Al-Dammam (Fig.1). Despite Ras Tanura's port area being situated on a narrow peninsula, Saudi Aramco has constructed several artificial islands to facilitate more effortless docking for contemporary oil tankers, which require deeper water. The sea-level change data pertains to the recorded hourly sea-level fluctuations from 2012 to 2021. The data were acquired from the Owner, General Authority for Survey and Geospatial Information (GEOSA) in Riyadh from 2012 to 2021. The recorded tide measurements are expressed in meters concerning the Lowest Astronomical Tide (LAT). The Local Auxiliary Tide (LAT) is 3.37 meters beneath the Primary Tide Gauge Benchmark (TGBM). The data retrieval rate exceeds 96%, and any missing values are filled using linear interpolation. The sea-level station is near Ras Tanura port, with the following geographic coordinates: 26° 39' 57.7" N; 50° 07' 54.2" E. The creek is well-suited for installing a sea-level gauge since it is shielded from the direct impact of wind and waves. The gadget has a precision of ± 0.005 m. Figure 2 Wind Rose (direction with speed) on an hourly and daily basis for 2016 and 2018. The wind rose diagrams in Figure 2 represent the direction that changes between the north and northwest of the sampling station for two years, 2016 and 2018. This shows that the coast is downwind of the coast for most of the year.

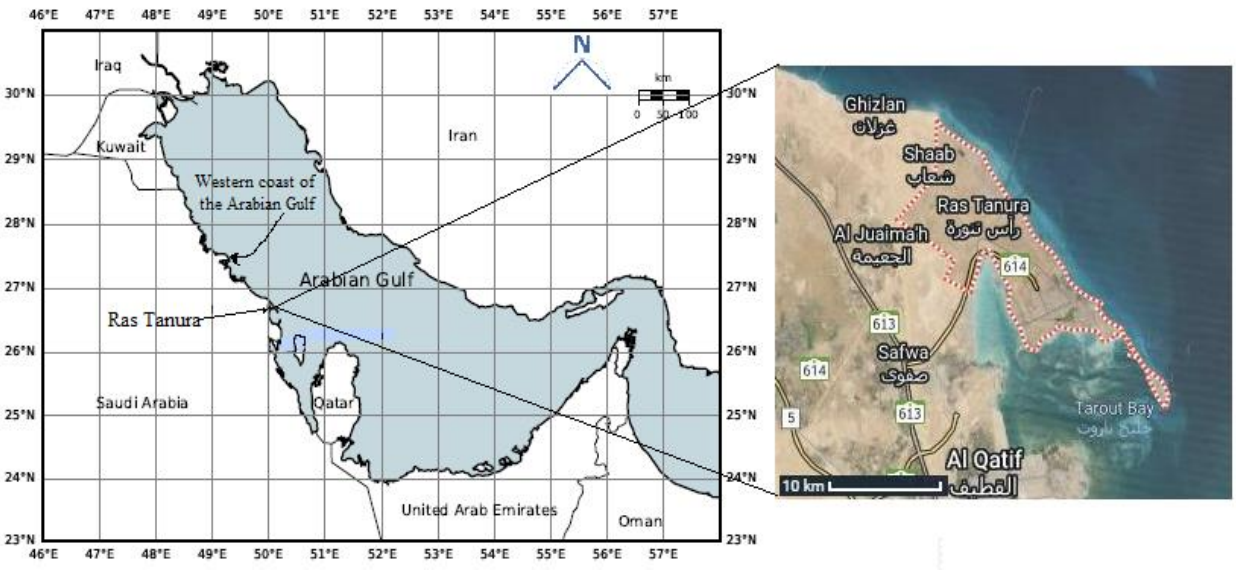

Figure 1. Location and Map of the Study Area

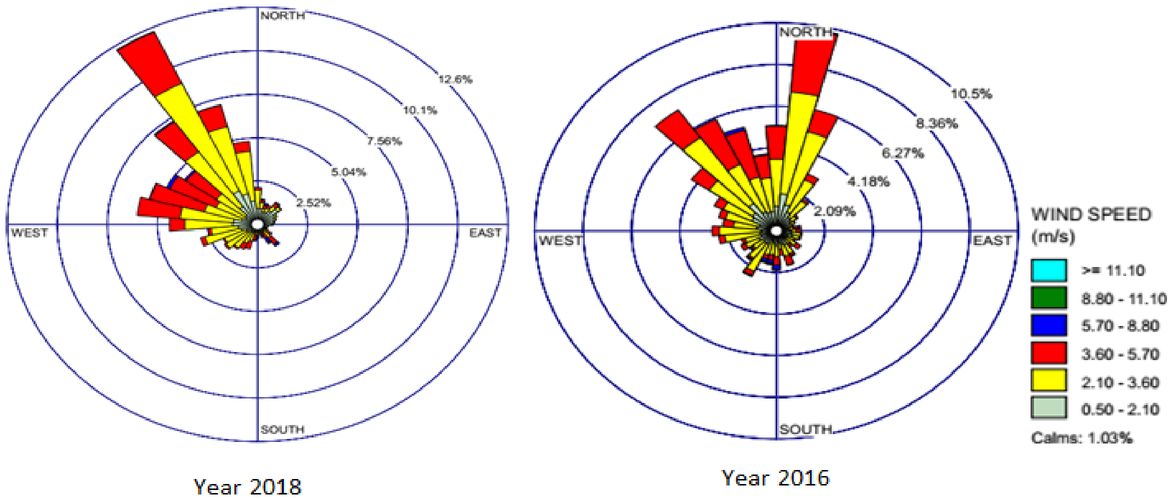

Figure 2. Wind Rose (Direction with Speed) Hourly and Daily for 2016 and 2018

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III. METHODS FOR DAILY TIDAL LEVEL PREDICTION

Machine learning (ML) concentrates on analyzing and creating a capable of learning from data, making forecasting on new data [10]. Artificial neural networks have recently outperformed numerous previous methods. Neural networks simulate the human brain's cognitive process by mapping output and input data [2]. The network undergoes learning by modifying the connections (referred to as weights) between layers. Once the network has received sufficient training, it can generate appropriate output for a given input data set by generalizing. Neural networks provide the advantageous generalization characteristic, allowing a trained network to accurately produce output data for a collection of input data that it has not encountered before. Learning usually occurs through training, where the training algorithm gradually modifies the connection weights (synapses).

Random Forest is a popular machine-learning method created by Leo Bierman and Adele Cutler [11]. It mixes the results of several decision trees to produce a single outcome. This tool's ease of use and adaptability have contributed to its widespread use, as it effectively tackles classification and regression difficulties. The subsequent instructions elucidate the functioning of the Random Forest Algorithm:

1- Choose samples from a provided dataset.
2- The model will generate a tree, which is called a decision tree, for each piece of the dataset.
3- Voting will occur by calculating the average decision tree.
4- Choose the predicted result with the highest number of votes as the ultimate result.

While random forests construct a collection of profound and separate trees, GBMs build a collection of shallow and weak consecutive trees, where each tree learns from and improves upon the previous one. The aggregation of numerous weak individual trees results in a formidable "committee" that is frequently difficult to outperform using alternative techniques. The primary concept behind boosting is to successively include new models in the ensemble. During each iteration, a new weak base-learner model is trained to minimize the error of the ensemble learned up to that point. The (k-NN) is a non-parametric supervised learning technique initially created by Evelyn Fix and Joseph Hodges [12] in 1951 and subsequently extended by Cover [13]. It is employed for categorization and estimation. Both scenarios input the k-nearest training examples from a given data set. The outcome is contingent upon whether k-NN is used for classification or regression purposes:

1. The outcome of k-NN classification is assigning an instance to a particular class. An item is categorized based on a majority vote among its neighboring objects. The object is assigned to the class most frequently represented among its k closest neighbors (k is a small positive whole number). When k is equal to 1, the object is assigned to the class of its closest neighbor.
2. In k-NN regression, the output corresponds to the attribute's value associated with the object. The value represents the mean values of the k nearest neighbors. When k is equal to 1, the output is assigned to the value of the nearest neighbor.

IV. DATA CRITERIA FOR (MLAs) PERFORMANCE

Machine learning algorithms (MLAs) like (ANNs), (RF), (KN), and (GBM) are effective data-driven techniques that are not commonly employed for predicting tidal-level productivity. Therefore, a comprehensive comparative evaluation of these methods in this field is lacking. The MLAs' performances in predicting daily tidal levels are compared using various metrics such as (MAE) Eq.1, (MSE) Eq.2, (NMSE) Eq.3, (MAPE) Eq.4, (R) Eq.5, and (RMSE) Eq.6. A specific level of data processing is necessary before presenting the training patterns to the MLAs. The performance of the MLA model was evaluated using several metrics, including the (MAE), (MSE), (NMSE), (MAPE), (R), and (RMSE).

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |P_i - O_i|^2 \qquad (1)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (P_i - O_i)^2 \qquad (2)$$

$$NMSE = \frac{1}{N}\sum_{i=1}^{N} \frac{(P_i - O_i)^2}{\bar{P}\bar{O}} \qquad (3)$$

$$MAPE = \left[\frac{1}{N}\sum_{i=1}^{N} \left|\frac{(P_i - O_i)}{P_i}\right|\right] \times 100 \qquad (4)$$

$$R = \frac{\sum_{i=1}^{N}(P_i - \bar{P})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{N}(P_i - \bar{P})^2 \sum_{i=1}^{N}(O_i - \bar{O})^2}} \qquad (5)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \qquad (6)$$

Where the predicted value is Pi, the observed value is Oi, the mean value for the observed data is the mean value for the predicted data, and the number of observations is *N*.

V. RESULTS AND DISCUSSION

The inputs of the MLA methods consist of the preceding observations of daily tidal levels. By varying the amount of previous daily tidal level measurements, it was determined that the optimal outcome could be obtained by utilizing only eleven past tidal level values. Including more data from prior periods did not alter the outcome. Four models were compared to find the most suitable Machine Learning Algorithm (MLA) for the data on sea levels of the daily tidal. Multiple trainings were conducted to ascertain the optimal number of hidden layers and neurons in the hidden layers, resulting in the highest performance of the testing process for the Random Forest (RF), K-Nearest Neighbors (KN), Gradient Boosting Machine (GBM), and Artificial Neural Network with Multilayer Perceptron (ANN-MLP). Table 1 displays the training parameters utilized in the MLA models. The most effective training process for every situation has also been identified. The algorithm accuracy was assessed by using the (MAE), (MSE), (NMSE), (MAPE), (R), and (RMSE) metrics. Table 2 presents the obtained results for the (RF), (KN), (GBM), and (ANN-MLP) models. The table includes the (MAE), (MSE), (NMSE), (MAPE), (R), and (RMSE) metrics. These metrics were calculated using each model's training and testing data subsets. During the training phase of various Machine Learning Algorithms (MLAs), it is shown that all of them effectively approximated the pattern of the subset of data.

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The training dataset is more effectively suited to the various machine learning methods when comparing the outcomes during the testing process. Table 2 displays the outcomes of the model for various Machine Learning Algorithms (MLAs).

Table 1 Model Parameters of the Machine Learning Algorithms (MLAs) used for the Testing and Training

Models	Parameters
(RF),	The input tide values have been calculated every hour since 2012 (from 31 January). The utilized method is Random Forest Regression (RF). The data was split into 70% for training the model and 30% for testing. Number of trees = 50; Maximum depth of each tree = 10; Minimum number of samples required to split a node = 2; Minimum number of samples needed for each leaf node = 1
(KN),	The input tide values have been calculated every hour since 2012 (starting 31 January). The utilized method is K-Nearest Neighbors Regression (KN); the number of neighbors is 6. The data was split into 70% for training the model and 30% for testing.
(GBM)	The input tide values are calculated due to 2012 (starting from 31 Jan) every one hour. The utilized method is Gradient Boosting Machines (GBM). The data has been split into 70% for training the model, 30% for testing, Random state=42
(ANN-MLP) model	Criteria input for the utilized ANN-MLP: three hidden layers with 150 and 100,50 neurons, respectively.; The maximum iterations =300. The activation function is "tanh".

Table 2 Performance of the MLAs Models

a. ANN-MLP Model				
Testing			**Training**	
NMSE:	0.070194		NMSE:	0.061311
MAE:	0.094697		MAE:	0.093541
MSE:	0.017726		MSE:	0.016007
RMSE:	0.133138		RMSE:	0.12652
R-Squared:	0.929806		R-S:	0.938689
MAPE	**10.95%**		**MPAE**	**10.09%**
b. RF Model				
Testing			**Training**	
NMSE:	0.083316		NMAE:	0.012203
MAE:	0.11488		MAE:	0.044354
MSE:	0.021039		MSE:	0.003186
RMSE:	0.145048		RMSE:	0.056444
R-Squared:	0.916684		R-S:	0.987797
MAPE	**12.52%**		**MPAE**	**4.62%**
c. KN Model				
Testing			**Training**	
NMSE:	0.099485		NMSE:	0.060444
MAE:	0.123331		MAE:	0.098562
MSE:	0.025122		MSE:	0.015781
RMSE:	0.158499		RMSE:	0.125623
R-Squared:	0.900515		R-S:	0.939556
MAPE	**13.28%**		**MPAE**	**10.17%**
d. GBM Model				
Testing			**Training**	
NMSE:	0.091521		NMSE:	0.033267
MAE:	0.118208		MAE:	0.071166
MSE:	0.023111		MSE:	0.008685
RMSE:	0.152023		RMSE:	0.093196
R-Squared:	0.908479		R-S:	0.966733
MAPE	**10.98%**		**MPAE**	**6.51%**

Table 2 demonstrates that the training subset exhibits lower values for MAE, MSE, NMSE, MAPE, and RMSE than most models' testing subsets. The four- MLA models yielded higher *R* values, ranging from 0.900515 to 0.929806 for the testing subset and from 0.938689 to 0.987797 for the training subset. Upon comparing the outcomes of several methods, it was discovered that the ANN-MLP exhibited the lowest values for MAE, MSE, NMSE, MAPE, and RMSE during the training process while achieving the highest value for R during the testing process. The ANN-MLP achieved the lowest error with the following values: 0.094697 m for MAE, 0.017726 m for MSE, 0.070194 m for NMSE, 10.95% for MPAE, 0.929806 for R, and 0.133138 for RMSE. The ANN-MLP achieved the highest accuracy, accompanied by the lowest root mean square error values (Table 2 (a). The achieved findings for the ANN-MLP are graphically displayed in Figures 3, 7, and 8. The selection of MLAs for forecasting daily tidal levels should be based on the one with the lowest errors, as it is a reliable global estimator. The analysis revealed that the ANN-MLP had superior accuracy in the testing groups see Table 2(a) while RF had superior accuracy in the training process see Table 2(b). Most of the error values for all models, representing the disparity between the observed and predicted tidal levels, are within the range of -0.04 m to +0.04 m see Figures 3,4,5 and 6. Unlike the findings obtained for the ANN-MLP network, the KN demonstrated the lowest level of accuracy see Table 2 (c). The KN achieved the highest error with the following values: 0.123331 m for MAE, 0.025122 m for MSE, 0.099485 m for NMSE, 13.28% for MPAE, and 0.158499 for RMSE. Figures 4,5 and 6 show residual error between the observed and predicted tidal levels for the RF, KN, and GBM, respectively. The findings indicate that the utilization of ANN-MLP leads to a substantial decrease in the overall inaccuracies in forecasting daily tide levels. The discrepancy in tidal level between the observed data and the findings of the ANN-MLP model exhibits a consistent pattern. The ANN-MLP achieved a reduction in RMSE of 8.945%, 19.05%, and 14.18% compared to (RF), (KN) and (GBM), respectively, during the testing process. The ANN-MLP demonstrated the best level of accuracy, together with the lowest values for Root Mean Square Error. This experiment proves that the ANN-MLP method can be utilized as a supervised machine learning method for accurately forecasting seawater levels of tidal.

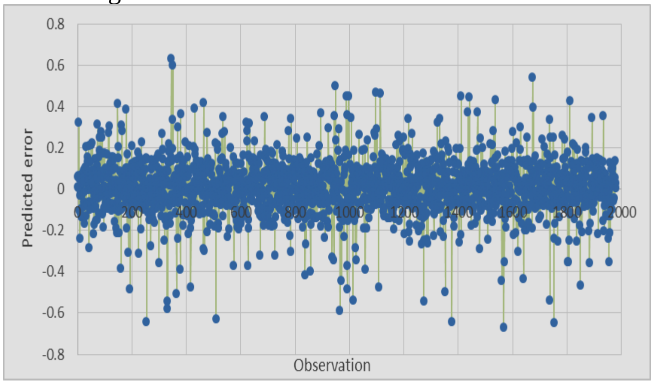

Figure 3 Residual Error Between the Predicted and Observed Data of Tidal Levels by Using the Ann-Mlp Method

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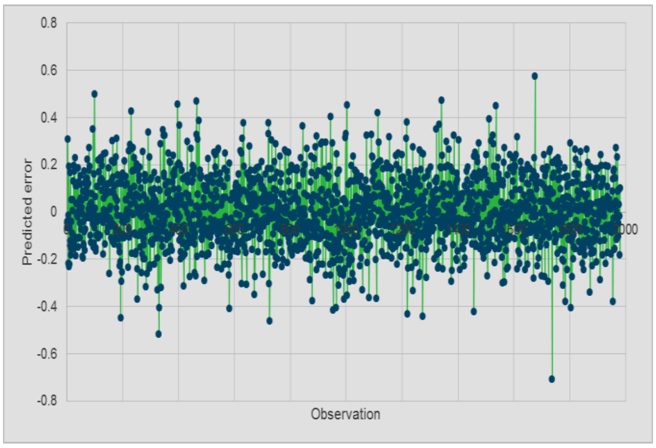

Figure 4 Residual Error Between the Predicted and Observed Data of Tidal Levels by Using the Rf Method

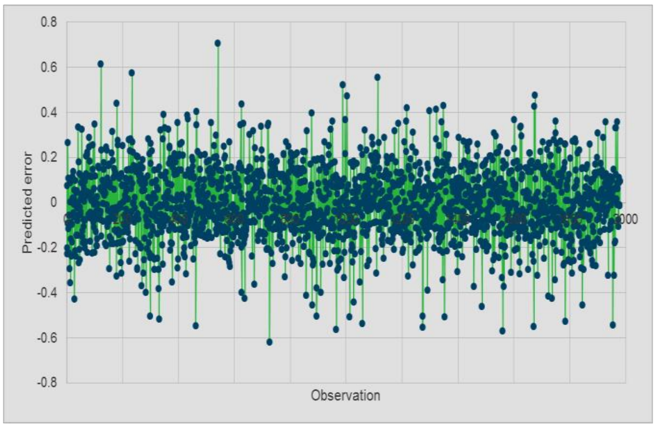

Figure 5 Residual Error Between the Predicted and Observed Data of Daily Tidal Levels by Using the Kn Method

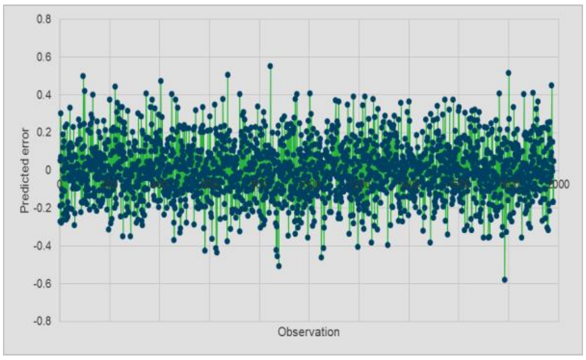

Figure 6 Residual Error Between the Predicted and Observed Data of Tidal Levels by using the GBM Method

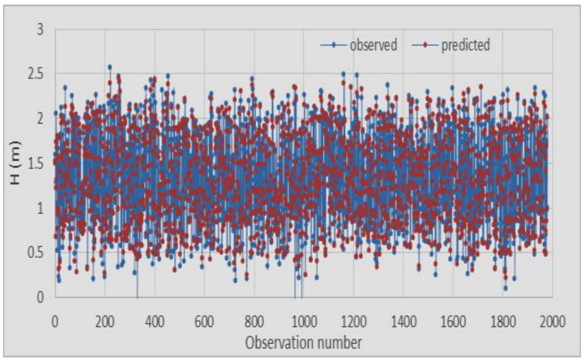

Figure 7 Observed and Predicted Data Comparison of the Tidal Level Forecasted using the ANN-MLP

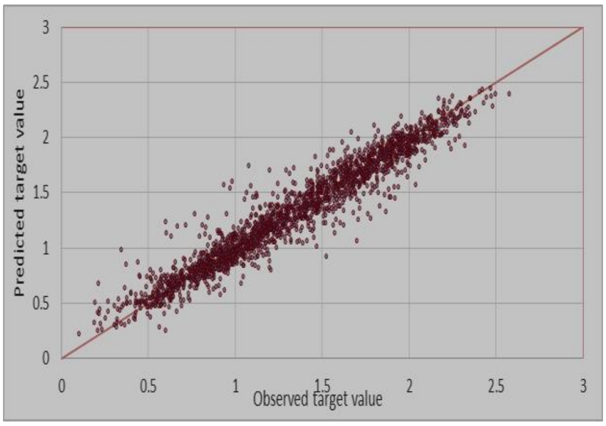

Figure 8 Observed and Predicted Tidal Level Values by the ANN-MLP (Scatter Plot)

VI. CONCLUSIONS

Accurate prediction of tidal levels is crucial for designing and constructing marine buildings. Four Machine learning algorithms, including random forest (RF), k-nearest neighbors (KN), gradient boosting machine (GBM), and multilayer perceptron (ANN-MLP), were introduced to explore an efficient strategy for predicting tide levels along the central coast of the western Arabian Gulf. Machine learning models can perform well because they have the main advantage of being universal function approximators, even for non-linearity cases. The findings suggest that the ANN-MLP model accurately predicts tidal levels, whereas the RF model exhibits the lowest accuracy. The ANN-MLP model outperformed the Random Forest Regression (RF), K-Nearest Neighbors Regression (KN), and Gradient Boosting Machines (GBM) models in terms of RMSE on the training data. The results verify that the ANN-MLP model provides improvements in RMSE of 8.945%, 19.05%, and 14.18%, compared to (RF), (KN), and (GBM), respectively, throughout the testing process. The ANN-MLP demonstrated the best level of accuracy, together with the lowest values for Root Mean Square Error RMSE. The study's findings suggest that the ANN-MLP model is a viable technique for predicting tidal levels.

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Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material	Not relevant.
Authors Contributions	I am only the sole author of the article.

REFERENCES

1. Shu J.J., Prediction and Analysis of Tides and Tidal currents. The International hydrographic review, 4, 2, 2003.

2. Ha, N.T.; Manley-Harris, M.; Pham, T.D.; Hawes, I. A Comparative Assessment of Ensemble-Based Machine Learning and Maximum Likelihood Methods for Mapping Seagrass Using Sentinel-2 Imagery in Tauranga Harbor, New Zealand, Remote Sens., **2020**, 12, 3, 1-16. https://doi.org/10.3390/rs12030355
3. Haykin S., Neural networks: A Comprehensive Foundation, 1994, Prentice Hall PTR.
4. Vaziri M., Predicting Caspian Sea Surface Water Level by ANN and ARIMA Models, Journal of waterway, port, coastal, and ocean engineering, 123, 4, 1997, 158-162. https://doi.org/10.1061/(ASCE)0733-950X(1997)123:4(158)
5. Liu, J.; Shi, G.; Zhu, K. High-Precision Combined Tidal Forecasting Model. Algorithms, 12, 3, 2019, pp.1-17. https://doi.org/10.3390/a12030065
6. Tsai C.P., and Lee T.L., Back-Propagation Neural Network in Tidal-Level Forecasting, Journal of Waterway, Port, Coastal, and Ocean Engineering, 125, 4, 1999, 195-202. https://doi.org/10.1061/(ASCE)0733-950X(1999)125:4(195)
7. Rodriguez-Galiano, V., Sanchez-Castillo, M., Chica-Olmo, M., & Chica-Rivas, M., Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees, and support vector machines, Ore Geology Reviews, 71,**2015**, 804-818. https://doi.org/10.1016/j.oregeorev.2015.01.001
8. Steidley C., Sadovski A., Tissot P., Bachnak R., and Bowles Z, Using an Artificial Neural Network to Improve Predictions of Water Levels Where Tide Charts Fail, in International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, 2005. https://doi.org/10.1007/11504894_83
9. Alshahri, Fatimh, et al. "Investigation of Natural Radioactivity Levels and Evaluation of Radiation Hazards in Residential-Area Soil Near a Ras Tanura Refinery, Saudi Arabia." Polish Journal of Environmental Studies, 28, 1, 2019. https://doi.org/10.15244/pjoes/83611
10. Pashova L., and Popova S., Daily Sea Level Forecast at Tide Gauge Burgas, Bulgaria Using Artificial Neural Networks, Journal of sea research, 66, 2, 2011,.154-161. https://doi.org/10.1016/j.seares.2011.05.012
11. Breiman L., Random Forests, Machine Learning, 45, 1,**2001**,.5–32. https://doi.org/10.1023/A:1010933404324
12. Fix, Evelyn; Hodges, Joseph L., Discriminatory Analysis. Nonparametric Discrimination: Consistency Properties (Report). USAF School of Aviation Medicine, Randolph Field, Texas. 1951. https://doi.org/10.1037/e471672008-001
13. T. Cover and P. Hart, Nearest neighbor pattern classification, IEEE Transactions on Information Theory, 13, 1, 1967, 21-27. https://doi.org/10.1109/TIT.1967.1053964
14. Kumar, P., & Rawat, S. (2019). Implementing Convolutional Neural Networks for Simple Image Classification. In International Journal of Engineering and Advanced Technology (Vol. 9, Issue 2, pp. 3616–3619). https://doi.org/10.35940/ijeat.b3279.129219
15. Reddy, M. V. K., & Pradeep, Dr. S. (2021). Envision Foundational of Convolution Neural Network. In International Journal of Innovative Technology and Exploring Engineering (Vol. 10, Issue 6, pp. 54–60). https://doi.org/10.35940/ijitee.f8804.0410621
16. B, Mr. K., Balasaran, M., Vishwanath, K. G., SK, R., & Samuel, B. J. (2020). A Dynamic Multi Label Image Classification based on Recurrent Neural Networks. In International Journal of Recent Technology and Engineering (IJRTE) (Vol. 8, Issue 6, pp. 5093–5096). https://doi.org/10.35940/ijrte.f9817.038620
17. Konduri, R. R., Roopavathi, N., Lakshmi, B. V., & Chaitanya, P. V. K. (2024). Mitigating Peak Sidelobe Levels in Pulse Compression Radar using Artificial Neural Networks. In Indian Journal of Artificial Intelligence and Neural Networking (Vol. 3, Issue 6, pp. 12–20). https://doi.org/10.54105/ijainn.f9517.03061023
18. Sharma, D., & Sharma, Dr. P. (2021). Design and Implementation of Rainfall Prediction Model using Supervised Machine Learning Data Mining Techniques. In Indian Journal of Data Mining (Vol. 1, Issue 2, pp. 20–26). https://doi.org/10.54105/ijdm.b1615.111221

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