Tikrit Journal of Engineering Sciences (2023) 30 (4): 74-87
DOI: http://doi.org/10.25130/tjes.30.4.9

IRAQI Academic Scientific Journals

College of Engineering

ISSN: 1813-162X (Print); 2312-7589 (Online)
Tikrit Journal of Engineering Sciences
available online at: http://www.tj-es.com

TJES Tikrit Journal of Engineering Sciences

Application of Machine Learning for Daily Forecasting Dam Water Levels

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Keywords:

Bagged Tree Model; Predictions; Machine Learning; Water Levels; Water Supply.

ARTICLE INFO

Article history:

Received	21 July	2023
Received in revised form	06 Sep.	2023
Accepted	04 Oct.	2023
Final Proofreading	20 Nov.	2023
Available online	25 Nov.	2023

Citation: Almubaidin MA, Ahmed AN, Winston CAA, El-Shafie A. **Application of Machine Learning for Daily Forecasting Dam Water Levels**. *Tikrit Journal of Engineering Sciences* 2023; **30**(4): 74-87.
http://doi.org/10.25130/tjes.30.4.9

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Abstract: The evolving character of the environment makes it challenging to predict water levels in advance. Despite being the most common approach for defining hydrologic processes and implementing physical system changes, the physics-based model has some practical limitations. Multiple studies have shown that machine learning, a data-driven approach to forecast hydrological processes, brings about more reliable data and is more efficient than traditional models. In this study, seven machine learning algorithms were developed to predict a dam water level daily based on the historical data of the dam water level. Multiple input combinations were investigated to improve the model's sensitivity, and statistical indicators were used to assess the reliability of the developed model. The study of multiple models with multiple input scenarios suggested that the bagged trees model trained with seven days of lagged input provided the highest accuracy. The bagged tree model achieved an RMSE of 0.13953, taking less than 10 seconds to train. Its efficiency and accuracy made this model stand out from the rest of the trained model. With the deployment of this model on the field, the dam water level predictions can be made to help mitigate issues relating to water supply.

تطبيق التعلم الآلي للتنبؤ اليومي بمستويات مياه السدود

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الخلاصة

إن الطبيعة المتطورة للبيئة تجعل من الصعب التنبؤ بمستويات المياه مقدما. على الرغم من كونه النهج الأكثر شيوعًا لتحديد العمليات الهيدرولوجية وتنفيذ تغييرات النظام الفيزيائي، فإن النموذج القائم على الفيزياء له بعض القيود العملية. وقد أظهرت دراسات متعددة أن التعلم الآلي، وهو نهج يعتمد على البيانات للتنبؤ بالعمليات الهيدرولوجية، يوفر بيانات أكثر موثوقية وأكثر كفاءة من النماذج التقليدية. في هذه الدراسة، تم تطوير سبع خوارزميات للتعلم الآلي للتنبؤ بمستوى مياه السد يوميًا بناءً على البيانات التاريخية لمستوى مياه السد. تم فحص مجموعات مدخلات متعددة لتحسين حساسية النموذج، وتم استخدام المؤشرات الإحصائية لتقييم موثوقية النموذج المطور. أشارت دراسة نماذج متعددة ذات سيناريوهات إدخال متعددة إلى أن نموذج الأشجار المعبأة في أكياس، والذي تم تدريبه على سبعة أيام من المدخلات المتأخرة، قدم أعلى دقة. حقق نموذج الشجرة المعبأة في كيس قيمة RMSE قدرها ٠,١٣٩٥٣، واستغرق تدريبه أقل من ١٠ ثوانٍ. كفاءته ودقته جعلت هذا النموذج متميزًا عن بقية النماذج المدربة. ومع نشر هذا النموذج على أرض الواقع، يمكن إجراء تنبؤات بمستوى مياه السد للمساعدة في تخفيف المشكلات المتعلقة بإمدادات المياه.

الكلمات الدالة: نموذج الشجرة المعبأة، التنبؤات، التعلم الالي، مستويات المياه، إمدادات المياه.

1.INTRODUCTION

Dams and reservoirs play an essential role in ensuring water resources are utilized for the benefit of the community. Hence, it is essential to predict the water level in a reservoir accurately to manage water resources as efficiently as possible [1,2]. The global issue of freshwater scarcity necessitates the development of native resolutions to comprehend the association between water supply and demand and respond effectively to local water shortages [3,4]. Human activities, including population growth and land-use changes driven by urbanization, industrialization, and agriculture, have exacerbated water scarcity [5,6]. The cumulative impacts of intensified land-use activities and climate change cast uncertainties on water resource availability, particularly by manipulating surface and groundwater hydrological regimes [7–9]. In this context, monitoring dam water levels is paramount for efficient dam operation and various applications such as reservoir management, understanding factors influencing water level variability, assessing climate change impacts on hydrological systems, and maintaining freshwater supply [10,11]. Comprehensive monitoring enables proactive decision-making, optimized water allocation, and adaptive strategies development to ensure sustainable water resource management amidst evolving environmental conditions [5,12]. Furthermore, accurate monitoring and forecasting of dam water level is critical because it affects parameters, such as dam inflows, dam water storage, and water release from dam reservoirs, evaporation, and infiltration [13,14]. These parameters define the dam reservoir uncertainties, which are critical in dam operations and modeling. The impact of dam water levels on rivers is multifaceted, encompassing environmental, hydrological, and climatic dimensions. Dams, primarily constructed for hydropower and water supply, threaten freshwater biodiversity and downstream ecosystems, affecting local communities and wildlife [15,16]. They disrupt river continuity, downstream flow, and water quality, with implications for flood control, water supply, navigation, and aquatic ecosystems [17–20]. The natural water level fluctuations impact water quality and aquatic communities, magnified when dams serve multiple non-seasonal purposes [21]. Additionally, dam water levels are essential for flood forecasting in semi-arid regions [22,23]. Climate change-induced rising sea levels further influence river salinity worldwide. Understanding these dynamics is crucial for informed water resource management in a changing environment [24]. The problem this research addresses is the need for proper water resource management, particularly in dams, considering the abundant rainfall in Malaysia and the potential risks associated with overflow caused by heavy downpours or sudden surges in water levels [25]. Dam systems are influenced by various external variables, such as weather conditions, climate patterns, water demand, and the presence of other dams in the scheme [26]. However, understanding the mechanisms and quantifying the effects of these variables individually and simultaneously can be challenging. While previous studies have focused on predicting dam water levels, few have quantified the strength and direction of the relationships between independent variables and dam levels [10]. Previous approaches relied on rule curves based on climatology, historical inflow analysis, and linear mathematical relationships based on operators' knowledge and experience [27], lacking the precision and adaptability required for sustainable dam management in the face of evolving environmental conditions. Therefore, the research aims to bridge this gap using data-driven machine learning models to enhance water level forecasting, offering a promising avenue for improved dam management practices and sustainable water resource management [28,29]. The progress and improvement of hydrological disciplines, which are vital for the efficient management of dams, rely heavily on the construction and effective operation of reservoirs. To enhance dam management practices, many forecasting models have been developed recently [30]. The primary objective of this research is to identify the most practical forecasting model for dam water level estimation. Additionally, the study aims to assess the feasibility and efficacy of utilizing artificial intelligence (AI) techniques in providing reliable and accurate information compared to conventional models. By exploring the potential of AI in the context of dam water level estimation, this research contributes to the advancement and optimization of reservoir design and operation, thereby facilitating sustainable water resource management. Novelty is further underlined through our focus on quantifying relationships between independent variables and dam water levels, an aspect often overlooked in previous studies. The practical implications of our research are substantial, promising more efficient dam management practices, optimized water allocation, and adaptive strategies. This study contributes to academic discourse through this innovation and offers tangible benefits for real-world water resource management. The research employed various machine learning models for daily dam water level forecasting. These models included linear regression, regression trees, support vector machines (SVM), gaussian process regression (GPR), kernel approximation regression, ensemble of trees, and neural networks (NN). The choice of employing multiple models was deliberate, allowing for a comprehensive evaluation of their performance and suitability for the specific forecasting task. Each model was assessed to determine its accuracy and effectiveness in predicting daily dam water levels. This study's diverse set of models provided valuable insights into the strengths and limitations of various machine learning approaches in the context of dam water level forecasting.

2. METHODOLOGY

2.1. Data Collection

The raw data obtained for this project consists of historical dam water levels in Durian Tunggal Reservoir, Melaka, from the 1st of January 1990 to the 30th of September 2019, with 8,362 rows of data. Table 1 outlines the summary of the water level data statistics. From this table, the mean of the water level data is 4.488 m, while the median and mode are 4.41 m and 4.21 m, respectively. The data standard deviation was quite low at 0.303812, which would affect the predicted data's correlation later. Also, the range of the data is relatively small at 2.74 m, although the data recorded spanned almost 20 years, which would also affect the training model, where it may not be able to predict a large range of values.

Table 1 Summary of Water Level Statistics.

Water Level Statistics	
Mean	4.488
Standard Error	0.003322
Median	4.41
Mode	4.27
Standard Deviation	0.303812
Sample Variance	0.092302
Kurtosis	3.888060
Skewness	1.529234
Range	2.74
Minimum	3.94
Maximum	6.68
Sum	37528.82
Count	8362

In addition to the dam water levels, a request was made to the Department of Irrigation and Drainage (DID) Malaysia to acquire rainfall data from the same period. From the map of the surrounding location of the Durian Tunggal Dam, the nearest rainfall monitoring station was found to be at Ladang Sing Lian at Bahagian Garing, Melaka. However, out of the 10,956 rows of water levels given, 4,940 recorded "NaN – Not a Number," which means that the data was not recorded, whether due to faulty instruments or problems relating to data logging.

2.2. Data Partitioning

In this study, data analysis is crucial for evaluating the prediction model's performance. Approximately 80% of the available data will be dedicated to training the model, while the remaining 20% will be utilized to assess the accuracy and generalization ability of the model. To ensure a comprehensive evaluation, different input scenarios will be considered. The data will be carefully partitioned, organizing the lagged input based on desired combinations and enabling a robust examination of the model's predictive capabilities. The analysis of Table 2 provides valuable insights into the statistical properties of the training and test data sets. The mean between both data has little difference. However, standard deviation-wise, the training data had a larger value than the test data. Also, it can be observed that the training data range (2.74) is greater than that of the test data (2.27). Differences in range could affect the testing of the models' performance since the trained model may not fit the test data well due to the small proximity between the range of the two data sets.

Table 2 Summary of Statistics for Training Data and Test Data.

	Statistics - Training Data	Statistics - Test Data
Mean	4.4782	4.4163
Standard Error	0.0034	0.0039
Median	4.42	4.375
Mode	4.12	4.295
Standard Deviation	0.3132	0.1808
Sample Variance	0.0981	0.0327
Kurtosis	2.8022	17.5564
Skewness	1.2830	2.9020
Range	2.74	2.27
Minimum	3.94	4.05
Maximum	6.68	6.32
Sum	38929.2	9592.2
Count	8693	2172

2.3.Time Series Forecasting

Machine learning applications in many fields, including the assessment of time series data for image, finance, video, and others, depend on time series forecasting [31]. Time series forecasting tasks can be approached in various ways, including using traditional statistical methods, machine learning techniques, and deep learning techniques. Real-world time series data is frequently unstable, hardly predictable, and greatly skewed [32–34]. Its robustness declines when a model is exposed to complicated and noisy settings, especially when minor alterations or noises appear in the input data. The model's ability suffers to generalize as a result. Given that the data used to train the machine learning models are historical data of the dam water levels, the appropriate forecasting model to be defined for this study is time series [28].

2.4.Lag Features

To further increase the models' sensitivity, different scenarios involving lag-time input will be fed to the training model to attest to its accuracy to be used in the test data later. The lag input combinations were done based on a correlation study of the raw data [35,36]. The sample partial autocorrelation of the water level against lag time in Fig. 1 shows that there is a decrease in partial autocorrelation as the lag time increases and setting the standard deviation 2, the lag time of 1 day to 7 days was showing within the correlation range to the water level at present.

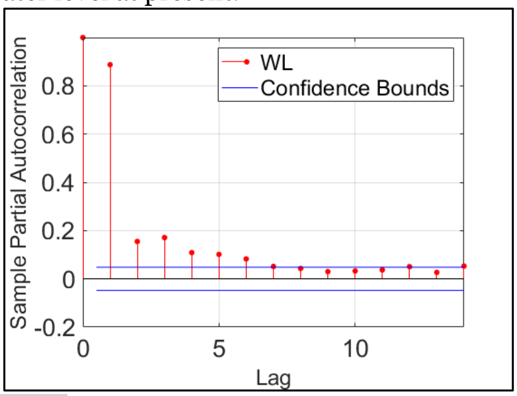

Fig. 1 Partial Autocorrelation of Water Level Data.

Hence, to assess the sensitivity of every model, four different input scenarios, as shown in Table 3, were studied based on multiple lag-time combinations.

Table 3 Input Data Lag-Time Scenarios.

Scenario	Input combination	Output
1	W.L.(t-1)	W.L.(t)
2	W.L.(t-1), W.L.(t-2) and W.L.(t-3)	W.L.(t)
3	W.L.(t-1), W.L.(t-2), W.L.(t-3), W.L.(t-4), and W.L.(t-5)	W.L.(t)
4	W.L.(t-1), W.L.(t-2), W.L.(t-3), W.L.(t-4), W.L.(t-5), W.L.(t-6), and W.L.(t-7)	W.L.(t)

2.5.Model Evaluation

2.5.1.Mean Absolute Error

Mean absolute error (MAE), mined as the dataset's overall alteration mean, describes the change between the initial and formulaic values. The formula for MAE as (Eq.1) [37,38]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - P_i| \quad \textbf{(1)}$$

Where O_i is the initial value at time i, and Pi is the result upon analysis/calculation.

2.5.2.Mean Square Error

The average of the squared errors obtained from the average squared difference between the predicted data and the observed data is measured by the Mean Square Error (MSE), an indicator for the predicting data. The formula for MSE is defined as (Eq.2) [38,39].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2 \quad \textbf{(2)}$$

2.5.3.Root Mean Square Error (RMSE)

The Root Mean Square Error (RMSE) is the residuals' standard deviation (forecast errors). Data points are separated from the regression line by residuals. To determine how these residuals are distributed, RMSE is calculated as (Eq.3) [38,40].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \quad \textbf{(3)}$$

2.5.4. Relative Error Percentage

The trained model chosen from each model is tested using the test data by estimating the percentage error. The percentage error of the simulated in the training phase is also calculated using (Eq.4) [41,42].

$$E\ (\%) = \frac{(Actual\ value - Predicted\ value)}{Actual\ value} \times 100\% \quad \textbf{(4)}$$

2.6. Method Flowchart

The proposed method flowchart for this study's model training and testing is shown in Fig. 2.

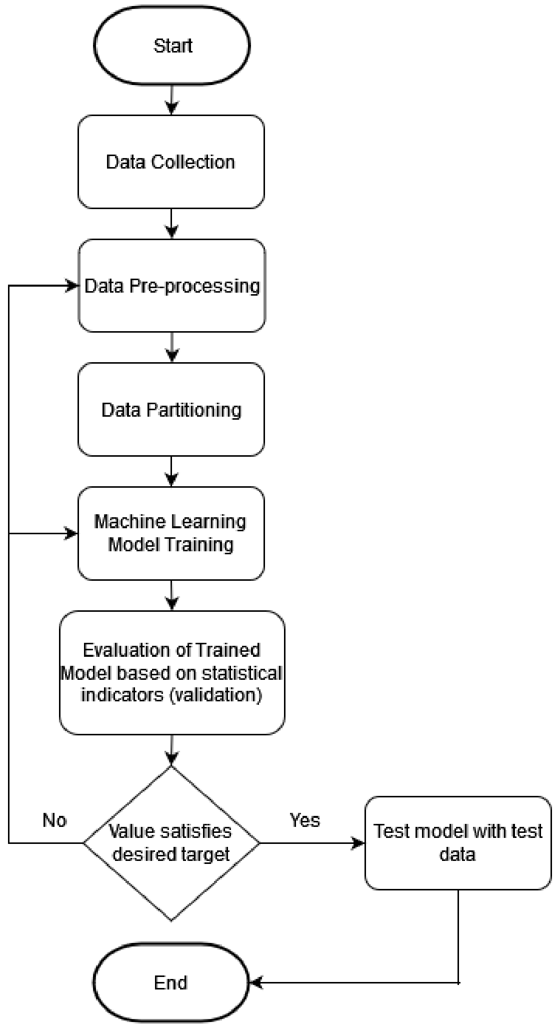

Fig. 2 Flow Chart of the Proposed Method in this Research.

3.RESULTS

The accuracies of different machine learning models, i.e., linear regression, regression trees, support vector machines, gaussian process regression, kernel approximation regression, ensemble of trees, and neural networks, were studied regarding their performance in forecasting daily dam water levels. The model was trained using data cleaned by replacing missing data with the average of the adjacent available values. RMSE is taken as the primary evaluation criterion, whereby the lower the value, the better the performance of the model is. Linear regression models, as shown in Table4, performed the best through the interactions linear (RMSE = 0.14372) technique. On the other hand, the robust linear technique showed the highest RMSE values, hence providing the worst performance among the linear regression models. However, both RMSE and MAE values exhibited by all the models are low, indicating high accuracies achieved. Comparing training time, the robust linear had the fastest training speed, although interactions linear was also comparable with a training time of less than 4 seconds. Stepwise linear had the second-best performance (RMSE = 0.14376), but it required the longest training time among the linear regression models at 36.83034 seconds. Within the interactions linear results, scenario 4 (lag 7) had the lowest RMSE, which was also observed in the other techniques except for robust linear, where scenario 1 (lag 1) resulted in the lowest RMSE. Hence, it can be said that greater numbers of lagged input results improved the model accuracy, such as observed from the interactions linear technique – the best-performing model for linear regression, the RMSE decreased from 0.15414 (scenario 1) to 0.14372 (scenario 4). The test statistics for regression trees models are laid out in Table 4 for their performance in forecasting daily dam water levels. Among all the techniques used in regression trees, the coarse tree model had the lowest RMSE values. In contrast to linear regression models, the lowest RMSE value in the coarse tree model was observed from scenario 2 (lag 3) instead of scenario 4 (lag 7). For the fine tree model, on the other hand, scenario 1 (lag 1) had the lowest RMSE, similar to the medium tree model, which shows that for the regression trees model, unlike linear regression, more lagged input unnecessarily improved the model accuracy. MAE-wise, lower scores were also observed, indicating high accuracies in the predicted data; however, the differences between the models and lagged input scenarios were only slight. Regarding training time, most regression trees models were trained below 3 seconds except for the fine tree model that was trained using scenario 3 (lag 5) input at 4.16650 seconds. The results for support vector machines (SVM) models, from Table 5, show that the Quadratic SVM technique best fit the data with an RMSE value of 0.14013, observed when the model was fed with scenario 3 (lag 5) data. The RMSE value for the Quadratic SVM model improved from scenario 1 (RMSE = 0.15179) through scenario 3 (RMSE = 0.14013); however, recorded a higher RMSE value for scenario 4 (RMSE = 0.14334). This observation indicated that the Quadratic SVM model performance may drop if lagged inputs exceed five days. Although Quadratic SVM had the best performance in terms of accuracy (RMSE), training of the model took some time, with training time ranging from 175.98614 seconds (scenario 1) to 772.64001 seconds (scenario 4). The fastest model for training among the SVM models was the coarse Gaussian SVM, with its lowest time record of 8.92334 seconds. In terms of worst performance, the Cubic SVM not only recorded a significant RMSE value at 0.39031 (scenario 2), but it also took the longest time to train, with training time ranging from 730.39128 seconds (scenario 3) to 827.29482 seconds (scenario 1). This observation indicates that the training time may not necessarily be affected by the number of lagged inputs but depends on the model type. Furthermore, the MAE values for cubic SVM models were not only the highest within the SVM models but also among all the machine learning models used, with the highest MAE recorded at 0.30239. The ensemble of trees models performance results are illustrated in Table 5. By analyzing the two techniques used under the ensemble of trees models, bagged trees indicated better performance with respect to RMSE, MAE, and MSE than the boosted trees model. When trained with scenario 4 (lag 7) input, bagged trees produced the best RMSE value (0.13953) compared to the rest. The trend in RMSE value for the bagged trees model showed increased performance as the number of lagged inputs increased. From scenario 1 (lag 1) to scenario 2 (lag 3), the RMSE decreased by 78.1%, then further decreased by 85.4% from scenario 2 to scenario 3 (lag 5). The RMSE decreased by 85.0% from scenario 3 to scenario 4 (lag 7), giving a value of 0.13953, the lowest RMSE value achieved among all the models. Regarding MAE, boosted trees had values in the range of 0.19347 (scenario 3) to 0.19571 (scenario 1), while bagged trees had values less than half of that, with the highest being 0.07068 (scenario 1) and the lowest being 0.06814 (scenario 4). Training time for the ensemble of trees models is also significantly better than the previous three models (SVM, GPT, and Kernel Approximation Regression), with the longest training time recorded being only 10.74819 seconds (bagged trees – scenario 3). Even with the best RMSE performance, bagged trees, when trained with seven days of lagged inputs, only took 9.98769 seconds to train. Table 6 outlines the performance of Gaussian Process Regression (GPR) models. It can be seen from the RMSE values that the best-performing model is the rational quadratic GPR with an RMSE of 0.14478 (scenario 3), while the worst-performing model is the Matern 5/2 GPR with an RMSE of 0.16456 (scenario 3). Lagged input wise showed similar observation with the SVM model with the rational quadratic GPR model, whereby scenario 3 (lag 5) gave the best performing model, and the RMSE improved from scenario 1 (0.15067) through scenario 3 (0.14478); however, increased again with scenario 4 (0.14585). Out of all the machine learning models used, GPR models took the longest train time, whereas even the fastest one (exponential GPR – scenario 2) took 299.94653 seconds to train. The best-performing technique (rational quadratic GPR) took the longest time to train at 656.97358 seconds (scenario 3). The GPR models performed well with low RMSE (0.14478-0.16456) and low MAE values (0.06981-0.09811). Table 6 shows a comparison between the Kernel Approximation Regression models. Two techniques were used, i.e., SVM kernel and least squares regression kernel. The latter proved to be the best model with an RMSE of 0.14772 scenario 2 (lag 3). Similar to regression trees models, the best performance came about when the model was fed-trained with three days of lagged input. By analyzing the RMSE for the least squares regression kernel, it increased to 0.16953 for scenario 3 and 0.17713 for scenario 4. The performance decreased when a lagged input of more than 3 was used. Although it was found to be the inferior model, the SVM kernel still had decent RMSE values within the range of 0.16394 (scenario 4) to 0.17500 (scenario 1). MAE-wise, several SVM and least squares kernel results exhibited values of more than 0.1 compared to some of the previous models. For both kernel models, training time was faster for scenario 1 input; however, the rest required more than 250 seconds to train. Table 7 shows the test performance for neural networks (NN) models in forecasting dam water levels. Five techniques of neural networks were used under this set of models, namely narrow NN, medium NN, wide NN, bilayered NN, and trilayered NN. Among these five models, trilayered NN produced the best results with an RMSE of 0.13963. The worst RMSE among the NN models was observed with wide NN with an RMSE of 0.15602. Analyzing the RMSE of trilayered NN, the trend in RMSE values decreased from scenario 1 (lag 1) to scenario 2 (lag 3) by 0.00902, then further decreased from scenario 2 to scenario 3 (lag 5) by 0.00229. However, the RMSE increased by 0.00230 to 0.14192 from scenario 3 to scenario 4 (lag 7). For MAE, the difference between all the models was minimal. Training time, however, differed across the NN models, with narrow NN having the fastest average training time of 35.26071 seconds, and the slowest one was recorded by wide NN with an average training time of 298.4019 seconds.

3.1.Analysis of Best Models

The analysis of the best models is further discussed in this section regarding the errors produced by the prediction model and their accuracies. The best models were chosen based on their RMSE values concerning the learning technique under each set of models and the number of lagged inputs used to train the particular model. To generate the residuals for the responses from each of the best models, the relative error percentage was calculated using (Eq. 4).

Table 4 Performance of Linear Regression and Regression Trees Models.

Linear Regression Models								
Scenario (Lag time)	**MAE**	**MSE**	**RMSE**	**Training time (s)**	**MAE**	**MSE**	**RMSE**	**Training time (s)**
Linear					**Interactions Linear**			
1 (1)	0.070	0.023	0.154	6.191	0.070	0.02376	0.154	1.627
2 (3)	0.071	0.021	0.147	6.030	0.073	0.02164	0.147	3.059
3 (5)	0.070	0.021	0.145	6.827	0.072	0.02080	0.144	3.219
4 (7)	0.069	0.020	0.144	5.969	0.071	0.02066	0.143	3.008
Robust Linear					**Stepwise Linear**			
1 (1)	0.06804	0.02551	0.15972	2.33835	0.070	0.023	0.154	1.128
2 (3)	0.07001	0.02727	0.16512	1.32472	0.073	0.021	0.147	3.247
3 (5)	0.07004	0.02734	0.16535	1.56779	0.072	0.020	0.144	9.318
4 (7)	0.07004	0.02734	0.16534	1.64564	0.071	0.020	0.143	36.830
Regression Trees Models.								
Fine Tree					**Medium Tree**			
1 (1)	0.070	0.022	0.151	1.696	0.070	0.023	0.153	1.147
2 (3)	0.083	0.026	0.161	1.576	0.078	0.024	0.155	1.183
3 (5)	0.085	0.026	0.163	4.166	0.076	0.024	0.155	0.953
4 (7)	0.085	0.026	0.163	2.659	0.082	0.024	0.156	1.144
Coarse Tree								
1 (1)	0.070	0.022	0.150	0.461				
2 (3)	0.071	0.021	0.147	2.861				
3 (5)	0.073	0.022	0.149	2.417				
4 (7)	0.074	0.022	0.149	0.774				

Table 5 Performance of Support Vector Machines (SVM) and Ensemble of Trees Models

Support Vector Machines (SVM) Models								
Scenario (Lag time)	**MAE**	**MSE**	**RMSE**	**Training time (s)**	**MAE**	**MSE**	**RMSE**	**Training time (s)**
Linear SVM					**Quadratic SVM**			
1 (1)	0.066	0.024	0.156	22.918	1 (1)	0.067	0.023	0.151
2 (3)	0.067	0.022	0.151	107.382	2 (3)	0.066	0.019	0.141
3 (5)	0.066	0.022	0.149	111.419	3 (5)	0.065	0.019	0.140
4 (7)	0.066	0.022	0.148	106.448	4 (7)	0.065	0.020	0.143
Cubic SVM					**Fine Gaussian SVM**			
1 (1)	0.067	0.023	0.151	175.968	0.066	0.022	0.149	9.793
2 (3)	0.066	0.019	0.141	735.656	0.067	0.021	0.146	12.186
3 (5)	0.065	0.019	0.140	691.765	0.071	0.021	0.148	12.952
4 (7)	0.065	0.020	0.143	772.640	0.078	0.023	0.151	14.663
Medium Gaussian SVM					**Coarse Gaussian SVM**			
1 (1)	0.065	0.022	0.151	9.285	0.066	0.022	0.151	8.923
2 (3)	0.062	0.020	0.142	10.068	0.063	0.020	0.141	10.505
3 (5)	0.062	0.020	0.142	9.292	0.063	0.020	0.141	10.224
4 (7)	0.063	0.020	0.142	9.218	0.063	0.020	0.141	8.940
Ensemble of Trees Models								
Boosted Trees					**Bagged Trees**			
1 (1)	0.195	0.055	0.236	6.574	0.070	0.023	0.151	5.411
2 (3)	0.193	0.054	0.234	4.748	0.070	0.020	0.141	6.578
3 (5)	0.193	0.054	0.233	5.641	0.069	0.019	0.140	10.748
4 (7)	0.193	0.054	0.234	4.684	0.068	0.019	0.139	9.987

Table 6 Performance of Gaussian Process Regression (GPR) and Least Squares Regression Kernel Models

Gaussian Process Regression (GPR) Models								
Scenario (Lag time)	**MAE**	**MSE**	**RMSE**	**Training time (s)**	**MAE**	**MSE**	**RMSE**	**Training time (s)**
Squared Exponential GPR					**Matern 5/2 GPR**			
1 (1)	0.070	0.022	0.150	311.315	0.069	0.022	0.150	338.093
2 (3)	0.071	0.022	0.148	323.190	0.071	0.022	0.148	326.542
3 (5)	0.073	0.022	0.150	346.844	0.098	0.027	0.164	391.514
4 (7)	0.072	0.021	0.148	346.812	0.093	0.026	0.162	390.422
Exponential GPR					**Rational Quadratic GPR**			
1 (1)	0.069	0.022	0.150	343.616	0.070	0.022	0.150	478.592
2 (3)	0.080	0.024	0.157	299.946	0.082	0.025	0.158	606.332
3 (5)	0.077	0.023	0.151	335.346	0.072	0.020	0.144	656.973
4 (7)	0.074	0.021	0.147	364.456	0.074	0.021	0.145	645.811
Least Squares Regression Kernel								
SVM Kernel					**Least Squares Regression Kernel**			
1 (1)	0.107	0.030	0.175	137.699	0.130	0.032	0.180	138.909
2 (3)	0.073	0.026	0.164	262.390	0.074	0.021	0.147	268.673
3 (5)	0.083	0.029	0.171	258.738	0.090	0.028	0.169	267.650
4 (7)	0.081	0.026	0.163	277.145	0.102	0.031	0.177	285.469

Table 7 Performance of Neural Networks (NN) Models.

Scenario (Lag time)	MAE	MSE	RMSE	Training time (s)	MAE	MSE	RMSE	Training time (s)
Narrow Neural Network					**Medium Neural Network**			
1 (1)	0.069	0.022	0.150	19.047	0.069	0.022	0.150	51.744
2 (3)	0.069	0.020	0.141	28.059	0.066	0.019	0.140	82.449
3 (5)	0.069	0.020	0.143	32.917	0.069	0.020	0.142	89.003
4 (7)	0.068	0.020	0.142	61.018	0.071	0.021	0.145	124.859
Wide Neural Network					**Bilayered Neural Network**			
1 (1)	0.069	0.022	0.150	213.787	0.070	0.022	0.150	74.559
2 (3)	0.073	0.022	0.149	301.326	0.069	0.020	0.141	163.370
3 (5)	0.074	0.022	0.150	311.964	0.069	0.019	0.141	157.697
4 (7)	0.080	0.024	0.156	366.529	0.068	0.019	0.140	177.217
Trilayered Neural Network								
1 (1)	0.070	0.022	0.150	133.197				
2 (3)	0.068	0.020	0.141	237.346				
3 (5)	0.066	0.019	0.139	229.250				
4 (7)	0.069	0.020	0.141	253.193				

With the relative error percentage, a graph was plotted using the relative error percentage to visualize the errors produced by the model for every predicted response. The maximum and minimum error percentages were also noted for each residual graph. In addition, a graph of predicted response against actual response was also plotted for each best-performing model with a diagonal line passing through the origin, indicating the perfect prediction of where all the plots were supposed to be if the model was perfect. The analysis of the results involved evaluating various models to predict dam water levels using different input combinations. The best performer among the linear regression models was the "interactions linear" model with scenario 4 (lag 7) lagged data as input. It achieved a prediction accuracy ranging from -22.8% to +30.7%, as shown in Fig. 3, illustrating the best models' residuals or relative percentage error. While most of the plots lie along the line of perfect prediction, outliers became more apparent when the actuals were greater than 4.5 m. The underestimation seemed more severe when the actuals were more than 5 m, where prediction values mainly lie below 5 m even with increasing actuals. The furthest outlier was (6.32, 4.379), which depicts the maximum relative percentage error of +30.7%, as shown in Fig. 4. In the regression trees models, the "coarse tree" with scenario 2 as input stood out as the top performer with an RMSE of 0.14770. Its prediction accuracy ranged from -26.4% to +30.1%, as shown in Fig. 3. Although the majority of the plots lie along the diagonal line of perfect prediction, outliers became more pronounced when the actuals were greater than 4.75 m and became more severe when the actuals were more than 5 m where more prediction values lie below 4.75 m even with increasing actuals. The furthest outlier was (6.32, 4.415), depicting the maximum relative percentage error of +30.1%, as shown in Fig. 4. Among the Support Vector Machines (SVM) models, the "quadratic SVM" with scenario 3 as input was the best model with an RMSE of 0.14770. It achieved a prediction accuracy ranging from -14.8% to +30.8%, as shown in Fig. 3. While most plots lay along the diagonal line of perfect prediction, more outliers become apparent when the actuals are greater than 5 m. Actuals greater than 5 m predicted a response of mostly below 4.75 m, and the furthest outlier was found to be (6.32, 4.373), which explains the maximum relative percentage error of +30.8%, as shown in Fig. 4. The Rational Quadratic Gaussian Process Regression (GPR) model that performed the best was the one with scenario 3 as input, achieving an RMSE of 0.14778. It provided a prediction accuracy ranging from -16.4% to +29.8%, as shown in Fig. 3. While most of the plots lay along the diagonal line of perfect prediction, more outliers become apparent when the actuals were greater than 5 m, where actuals of greater than 5 m had a predicted response of mostly below 4.8 m, and the furthest outlier was (6.32, 4.485), which explains the maximum relative percentage error of +29.0%, as shown in Fig. 4. Among the kernel approximation regression models, the "least square regression kernel" with scenario 2 as input emerged as the top performer with an RMSE of 0.14472. Its prediction accuracy ranged from -22.9% to +30.4%, as shown in Fig. 3. Although most plots lie along the diagonal line of perfect prediction, outliers became obvious when the actuals were greater than 4.8 m. The underestimation seemed more severe when the actuals were more than 5 m, where prediction values mostly lay below 4.8 m even as actuals increased. The furthest outlier was (6.32, 4.401), depicting the maximum relative percentage error of +30.4%, as shown in Fig. 4. In the ensemble of trees models, the "bagged trees" with scenario 4 as input was the best model with an RMSE of 0.13953. Its prediction accuracy ranged from -13.3% to +30.4%, as shown in Fig. 3. Although the majority of the plots laid along the diagonal line of perfect prediction and observably better than the previous other models, outliers became more apparent when the actuals were greater than 4.9 m and became more severe when the actuals were more than 5 m where more prediction values lay below 4.8 m even with increasing actuals. The furthest outlier was (6.32, 4.402), depicting the maximum relative percentage error of +30.4%, as shown in Fig. 4. Among the neural network (NN) models, the "trilayered NN" with scenario 3 as input achieved the best performance with an RMSE of 0.13963. Its prediction accuracy ranged from -20.8% to +30.5%, as shown in Fig. 3. Although most plots lay along the diagonal line of perfect prediction, outliers became obvious when the actuals were greater than 4.9 m. The underestimation seemed more severe when the actuals were more than 5 m, where prediction values mostly lay below 4.7 m even as actuals increased. The furthest outlier was (6.32, 4.392), depicting the maximum relative percentage error of +30.5%, as shown in Fig. 4. In summary, the analysis indicated that although the "bagged trees" and "trilayered NN" models performed relatively better with smaller RMSEs, they, like other models, tended to underestimate dam water levels, especially when they exceeded 5 meters. Further improvements may be needed to address this underestimation issue in future model development.

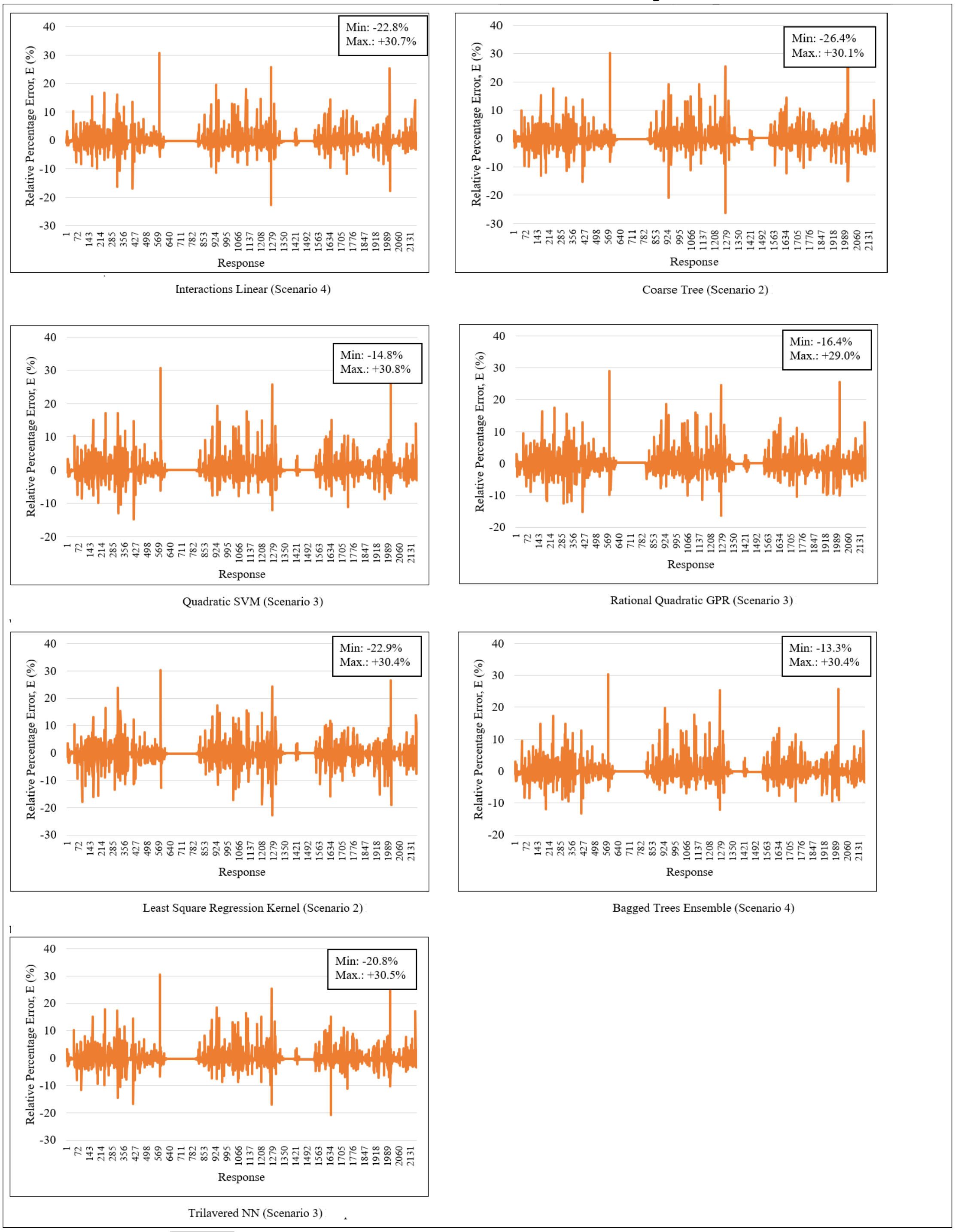

Fig. 3 Residuals for Best Models Responses for Best Models.

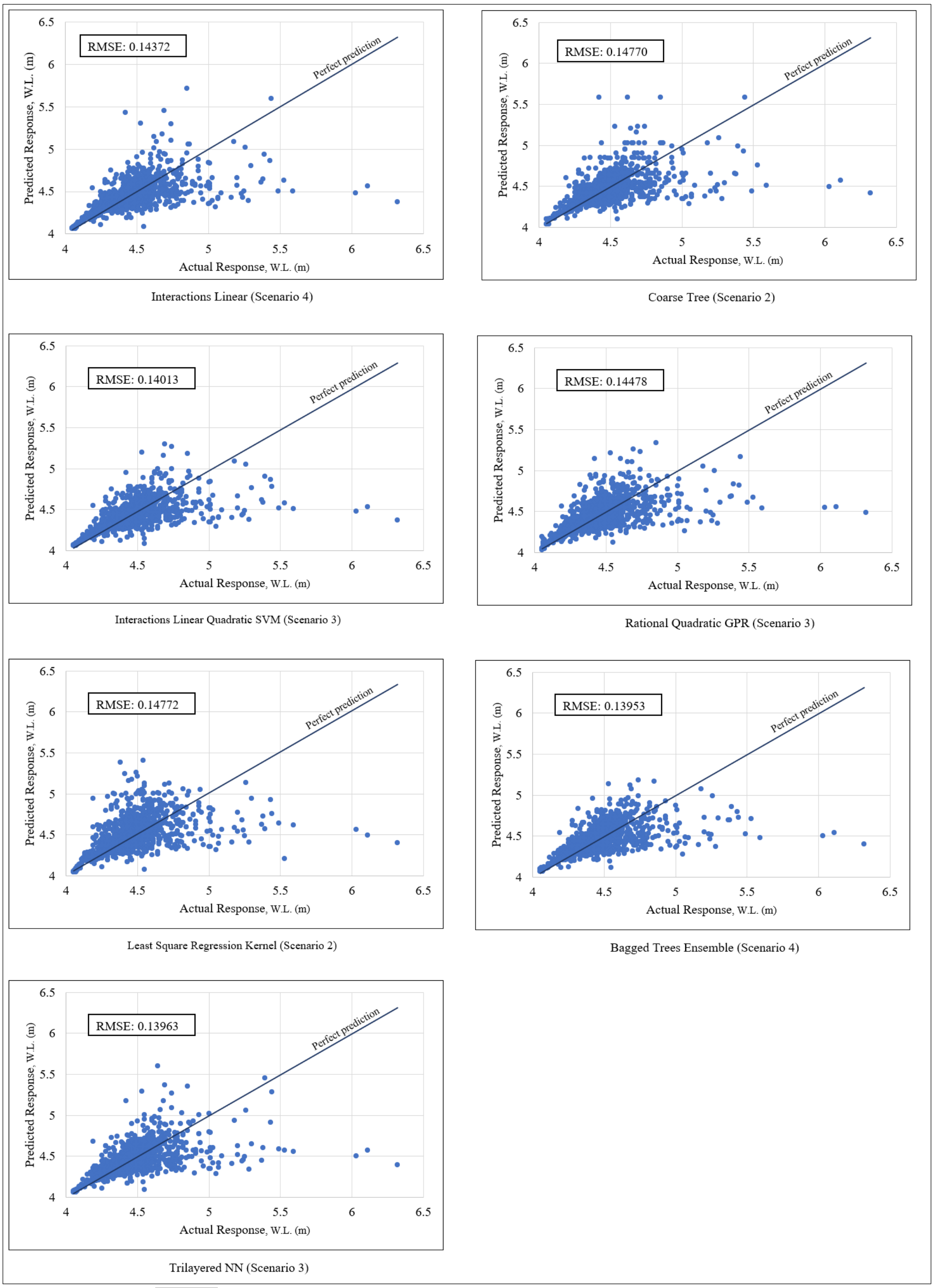

Fig. 4 Predicted Response vs. Actual Response for Best Models.

3.2.Summary of Results and Discussion

Among the models considered, the ensemble of bagged trees exhibited the most promising performance, achieving impressive metrics with an RMSE of 0.13953, MAE of 0.06814, and MSE of 0.01947. Notably, this high accuracy was obtained when the model was trained using a combination of lagged input variables within scenario 4. Comparatively, the nearest contender to the bagged tree model was the trilayered neural network (NN), which achieved an RMSE of 0.13963 when trained with input features from scenario 3. However, it is crucial to consider not only the predictive performance but also the computational efficiency of these models. In terms of training time, the bagged trees model demonstrated remarkable efficiency, requiring only 9.98769 seconds to train, even with a more extensive dataset featuring a 7-day lag. In stark contrast, the trilayered NN took a significantly longer time, clocking in at 229.25001 seconds for training with a 5-day lag input. This substantial difference in training times is a noteworthy factor for practical deployment. On the other hand, the cubic SVM model exhibited the poorest performance among all models, yielding an RMSE of 0.39031 when trained with input features from scenario 2. This cubic SVM model also required an extensive training time of 770.23084 seconds with the same input configuration. When comparing the RMSE of the worst-performing model (cubic SVM) with the best-performing model (bagged trees), a substantial 179.7% difference becomes apparent, underscoring the significance of model selection. To provide a comprehensive overview of the best-performing models across various machine learning techniques, it must also consider the rational quadratic GPR model, which yielded an RMSE of 0.14478. While this GPR model performed less favorably than the bagged trees, the difference in RMSE between the two models was comparatively modest, at 3.8%. Given its relatively competitive performance, this finding suggests that the GPR model might offer a viable alternative for specific applications. The present analysis highlights the bagged trees ensemble model as the standout performer in terms of predictive accuracy and training efficiency. However, further investigation is required to investigate the reasons behind the observed discrepancies and to elucidate their practical implications. Such insights can guide the selection of the most suitable model for specific applications and contribute to a deeper understanding of the predictive capabilities of these machine learning algorithms. Upon conducting correlation analysis through partial autocorrelation function, four different input scenarios were used to train each of the techniques under the seven groups of models. Analysis of the model performance indicated that the bagged trees under an ensemble of tree models provided the highest accuracy based on a few indicators. However, despite their high accuracies, all the models' underestimation tendency is still observed. This study affirms that developing machine learning models is possible with lagged historical data as input for training with a greater lag scenario providing better accuracy, as observed with the bagged trees model. Accurate predictions of dam water levels are attainable with most models. Still, low standard deviation in the raw data due to minimal data dispersion can lead to a less successful model development. Nonetheless, with the accuracy achieved, the model identified can be used to manage water resources for the dam reservoir's area and mitigate potential water-related risks. Using the model for daily forecast gives an idea of how much water will be left for consumption the next day, and this can help authorities prepare for any action required should the water be below minimum. Still, dam water levels should be monitored constantly since the forecast model, although accurate, is not perfect. One of the possible limitations of this study is the location of the study. While it has been proven many times that machine learning could successfully be used to predict water levels, the dam's location may play a role in whether training a model may be redundant. One of the reasons is that if there is a manual interference to the river flow, such as pumping in water from different river sources when the water level gets critical every day, the representation of how the water level behaves naturally has already been altered should such action is done on an inconsistent basis because machine learning is a data-driven method; therefore, it relies on the description of the trained data to develop itself. Furthermore, another limitation of this study is the consistency of data. Where the count was supposed to be 10,865 days between the start and end of the dataset, only 8,362 rows of data were recorded, which means that around 2,500 rows of data were not recorded and had to be replaced with another value. Similarly, this means that about 20% of the data were artificial and ineffectively represent the real situation of the water levels for the model to train on.

4.CONCLUSIONS

The present study investigates the capability of different machine learning models, namely, linear regression, regression trees, support vector machines (SVM), gaussian process regression (GPR), kernel approximation regression, ensemble of trees, and neural networks (NN) to forecast daily dam water levels specifically at Durian Tunggal Reservoir, Melaka. The choice of employing multiple models was deliberate, allowing for a comprehensive evaluation of their performance and suitability for the specific forecasting task. Each model was assessed to determine its accuracy and effectiveness in predicting daily dam water levels. The diverse set of models utilized in the present study provided valuable insights into the strengths and limitations of various machine learning approaches in the context of dam water level forecasting. Upon conducting correlation analysis through partial autocorrelation function, four different input scenarios were used to train each of the techniques under the seven groups of models. Analysis of the model performance indicated that the bagged trees under an ensemble of tree models provided the highest accuracy based on a few indicators. However, despite their high accuracies, all the models' underestimation tendency is still observed. The present study demonstrates the feasibility of developing machine learning models using lagged historical data as input, with a notable improvement in accuracy observed when employing a greater lag scenario, as exemplified by the bagged trees model. This research suggests that accurate predictions are achievable with various models, which can be valuable for managing water resources and mitigating risks. However, the study acknowledges limitations. The dam's location and potential manual interventions in river flow could affect model accuracy. Additionally, data consistency issues, with missing and artificially replaced data, may impact model training. Despite these limitations, with the accuracies achieved with the model, deployment is possible not only at the site of the study but also at other dams around Malaysia or in areas with similar climates and characteristics. Furthermore, integrating multiple sensors and input parameters such as rainfall and evaporation rate with the model can aid in the better forecast of dam water levels.

ACKNOWLEDGEMENTS

The authors thank the Department of Irrigation and Drainage Malaysia (JPS) for providing this study with the data.

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