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Research Article

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CNN-Bi LSTM Neural Network for Simulating Groundwater Level

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Keywords

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Groundwater level,
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Abstract

Managing groundwater resources affected by varying climatic conditions requires applying reliable and precise forecasts of groundwater levels. Hence, we investigated the implementation of deep learning neural network called CNN-Bi LTM, which combines convolutional neural network layers and bidirectional long-short term memory layers (Bi LSTM) models for forecasts of groundwater levels in a well affected by pumping for irrigation. The CNN-BiLSTM model was trained with hourly groundwater level data for Jan 2021 - Dec 2021, and the data was divided into 70% for training and 30% for testing. Besides, Bayesian optimization was used to find the best range of variables for the model, such as the number of Bi LSTM units, the number of Bi LSTM layers, and the initial learning rate. Also, the Adaptive Moment Estimation (Adam) is used to calculate adaptive learning rates. As a result, the model showed promising results in the taring stage with a regression value equal to 0.9173. In comparison, the model showed acceptable results in the testing stage with regression equal to 0.6324, and the optimization duration lasted for 21 hours. Further, the optimization method showed that the best number of Bi LSTM units is 192, the best number of Bi LSTM layers is two layers, and the best initial learning rate is 0.01.

1. Introduction

The groundwater extraction overextended the recharge rate in many countries worldwide, which led to various problems, such as water quality degradation and raised pumping fees [1–3] In addition, it has harmful effects in urban and agricultural regions [4], and water quality and water resource reliability availability monitoring have been the subject of many scientific studies [5–7]. Hence, it is essential to create a more valuable knowledge of the differences in groundwater levels to precisely emulate the groundwater level and properly manage groundwater resources [8].

Groundwater modeling is the many valuable standards of delivering information for groundwater management design because it can predict the potential trend of available groundwater resources [9], and conceptual or numerical models were commonly used to simulate the groundwater level as the primary study methods [10–13]. Nevertheless, these groundwater models have noticeable restrictions, such as simplifying complex dynamic procedures requiring enormous data and multiple input variables [14, 15]. In contrast, predicted groundwater levels can be acquired from restricted available data using AI approaches, which can be a practical option when attempting to comprehend the mechanisms governing the differences in groundwater water levels [16]. Besides, the development in soft computing applications like artificial intelligence (AI) and the availability of data acquired from field and computer simulations have supported researchers to employ AI approaches such as machine learning (ML) and deep learning (DL) methods to analyze collected data linked to the water resource management schemes [17–19]. Moreover,

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data-driven modeling approaches were improved rapidly for numerous research purposes [19, 20]. For example, various investigations involved ML and DL models in examining the predictive outcomes of multiple models in multiple fields such as hydrology and hydraulics [21, 22].

AI techniques such as optimization and deep learning were applied for various fields and simplified the solution [23–26]. For example, recurrent neural networks (RNN), an application of deep understanding, can deal with vast sequence data. Recurrent neural networks (RNNs) were adopted for simulating groundwater time series data [24, 27, 28] Still, it has been discovered that standard RNN contains the problem in catching long period dependencies between parameters due to two vanishing and exploding gradients, where weights in the neural network reach zero [29–31] Besides, the implementation of RNN in the precision of time series data has not been enhanced. In contrast, the variant of RNN is a long and short-term memory network (LSTM) showed an excellent performance to bypass the vanishing and exploding gradient issues, and LSTM can detour training issues by stopping unnecessary details from being handed to future model forms while keeping remembrance of significant past circumstances [32].

LSTM model has been successfully applied to groundwater depth level prediction [33]. [34] used the LSTM model to emulate the impacts of specified groundwater abstraction and rain on groundwater levels. [35] performed a process founded on Bidirectional Long Short-Term Memory (Bi-LSTM) to capture the Spatio-temporal process of groundwater with specified data. [36] used the LSTM to obtain lost data in groundwater records and noted that LSTM is suitable for repairing the GWL variation. [37] used the LSTM neural network to forecast ground-level forecasting. [18] used LSTM and back-propagation neural network (BP-ANN) for simulation of the groundwater level and showed that the LSTM provides good results for simulating the monthly groundwater level and is better than the BP-ANN model. [38] employed BiLSTM neural network model for modeling the monthly groundwater level.

Most AI approaches were used to simulate groundwater levels by employing precipitation, air temperature, evaporation, pumping rates, soil temperature, humidity, and wind speed [39, 40]. However, a few proposed models have been successfully predicted the groundwater level depending on the recorded groundwater level as the only input [41, 42]. Besides, a gap can be explored and studied more to improve the performance of machine learning models for modeling the groundwater level using only one input instead of different parameters as it is not easy to collect meteorological data. Therefore, the article aims to utilize only the hourly groundwater level data as input to simulate the groundwater level and examine the performance of a CNN - bidirectional LSTM neural network model (CNN-BiLSTM) for simulating measured groundwater level as there is not much research regarding the simulating of the groundwater level using deep learning models like LSTM or CNN-BiLSTM neural network with only groundwater level as input data. Besides, this study aims to demonstrate that the deep learning models can simulate groundwater levels by employing fewer input variables.

2. Methodology

2.1. CNN-Bi LSTM

Bidirectional -LSTM (Bi-LSTM) is a long-short term memory (LSTM) format, a special RNN. It transforms the separate activations into dependent activations function by giving all the layers the exact importance and biases and recognizing per prior result to deliver the following hidden layer as input. For example, in a straightforward RNN approach, at per iteration, t, the hidden layer persists a hidden state, ht, and updates and revs it according to the layer input, x_t, and prior hidden state, h_{t-1}, using the following Eq. (1) [35]:

$$h_t = \sigma_h(Wx_t + Vh_t - 1 - b_h) \tag{1}$$

W is the weight matrix provided from the input to the hidden layer, V is the weight matrix between two straight hidden conditions (h_{t-1} and h_t), b_h is the bias vector for the hidden layer, and σ_h is the activation function to develop the hidden form. The network output can characterize as Eq. (2) [35]:

$$y_t = \sigma_y(Uh_t + b_y) \tag{2}$$

U is the weight matrix from the hidden to the output layer, and σy is the activation function of the output layer. Eventually, the hidden layer provides the outcome yt. The LSTM layers process sequence data uni-directionally and limit it to catch the approach's randomness. Nevertheless, a backward LSTM layer can provide bi-directionally into the LSTM network. Therefore, designing a Bi LSTM layer including a forward LSTM layer and a backward LSTM layer functions sequence data with two different hidden layers and links them to the exact outcome layer [43]

Convolutional Neural Network (CNN) is a network model presented by [44], and it is a type of feed-forward neural network. It can be used to forecast time-series data [45]. The local perception and weight sharing of CNN can enormously decrease the number of parameters, hence enhancing the implementation of learning models. CNN includes the convolution, pooling, and complete connection layers [46], as shown in Figure 1. Per convolution layer encloses a prevalence of convolution kernels, and these layers drag the data feature. Its computation is as Eq. (3)

$$l_t = \tanh (x_t * k_t + b_t) \tag{3}$$

where l_t is the output value after convolution, tanh is the activation function, x_t is the input vector, k_t is the weight of the convolution kernel, and b_t is the bias of the convolution kernel [47].

The CNN neural network was adopted for various problems, and Figure 1 shows the structure of the CNN model [48]. [49] used the convolution neural network for handling classification problems to forecast pollution. [50] used the convolutional neural networks to create a flood vulnerability map. [51] used a CNN model to anticipate spatially distributed water for momentous overflow occasions. [52] used CNN and LSTM models to create a map for potential groundwater.

A CNN-LSTM model, as shown in Figure 2 integrates CNN layers that drag the feature from input data and LSTMs layers to supply series forecast, and it is commonly used for movement recognition. Their typical characteristics are designed to use visual time series forecast problems [53]. LSTM with convolutional neural network layers has been employed to encode spatiotemporal details for various purposes, like rainfall nowcasting [54]. Nevertheless, in hydrology, the applications of CNN-LSTM approaches have not been used to solve problems [55]. The detail for both CNN and Bi LSTM neural networks is explained in the literature broadly.

We employed in this study the CNN layer with the Bi LSTM layers model (CNN Bi-LSTM) for simulating hourly groundwater level data, as shown in Figure 2. Also, we used Bayesian optimization to find the best model for simulating groundwater levels. The detail of hyperparameters for the BI-LSTM model and the other parameters is illustrated in Table 1, and Figure 3 shows the modeling process.

The performance of CNN-Bi LSTM was evaluated based on:
Mean squared error (MSE)

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(T_K - O_K)^2 \tag{4}$$

where n is the number of data, O_K is the network outcome, T_K is the actual target.

Root mean squared error (RMSE):

$$RMSE = \sum_{k=1}^{n}\left(\frac{(T_{K} - O_K)^2}{n}\right)^{0.5} \tag{5}$$

Spearman's Rank-Order Correlation:

$$\rho = 1 - \frac{6\sum {d_i}^2}{n(n^2-1)} \tag{6}$$

where ρ is Spearman's rank correlation coefficient, d_i is the difference between the two ranks of each observation, and n is the number of observations.

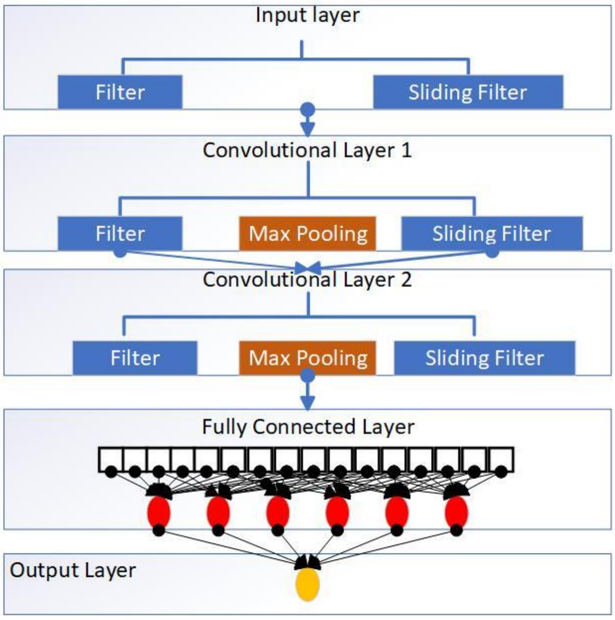

Figure 1. Overview of CNN architecture (Adopted from [48]).

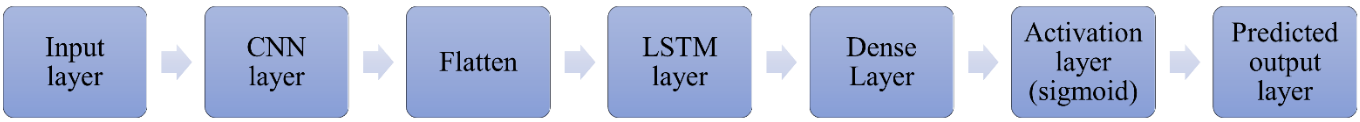

Figure 2. CNN-LSTM model (Adopted from [48]).

Table 1 CNN Bi-LSTM model.

The training parameters of the model		
Number of Bi-LSTM Layer	1 to 4	Hyperparameters
Number of Bi-LSTM Units	75 to 200	
Initial Learning Rate	0.01 to 1	
L2Regularization Rate	0.0000000001 to 0.01	
Number of Epochs	400	
Number of Iterations for Optimization	50	
Minimum Batch Size	60	
Training Optimizer	Adam	
Dropping Learning Rate During Training	Piecewise	
The factor for Learning Rate Dropping	0.5	

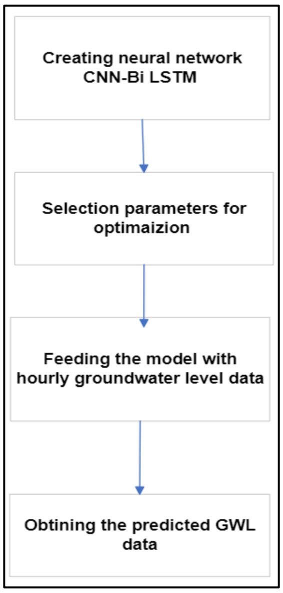

Figure 3 Modeling steps.

3. Data

The hourly groundwater data were collected from a CSD Interactive Data Map (Conservation and Survey Division/the University of Nebraska–Lincoln) [56], which provides real-time groundwater level data. Also, the collected data from a well affected by irrigation pumping. As shown in Figure 4, the groundwater level data is hourly data, and its unit is feet below the land surface for one year from 01/Jan/2021 to 30/Dec/2021. The data was divided into 70% for training (5845 data or from 01/ Jan / 2021 to 17/ Sep /2021) and 30% for testing (2509 data or from 18/Sep /2021 to 30/ Dec / 2021). It is essential to mention that the data did not normalize or standardized and used as raw data for training and testing the model.

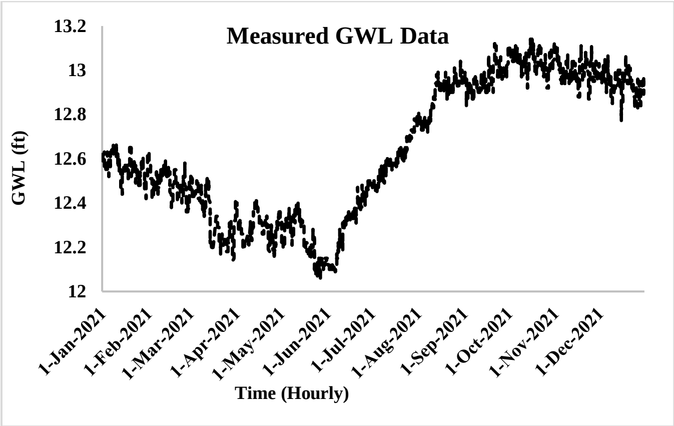

Figure 4 Groundwater level.

4. Result and Discussion

The optimized variables were obtained, as shown in Table 2, and the result of the model is from the best model. The best model is obtained after running the model for almost 21 hours with 50 iterations for the optimization process using a computer with Intel(R) Core (TM) i7-9750H (9 th Gen) CPU (2.60GHz) and RAM equal to 16 GB.

As shown in Figure 5, the model has shown good performance in the training stage with regression value (R^2) equals 0.9173, and rank correlation equals 0.9939 (Figure 6). While in the testing stage, the model showed acceptable performance with regression value (R^2) = 0.6324 and rank correlation = 0.9133, as shown in Figure 7 and Figure 8.

The test results are not too high, which can be attributed to the pumping, which the model could not catch the quick changes in the groundwater level. Still, the model can simulate the hourly groundwater level with high correlation and lower MSE error.

Table 2 Optimization of the model

Optimized Parameters	
Number of Bi-LSTM Layer	2
Number of Bi-LSTM Units	192
Initial Learning Rate	0.01
L2Regularization Rate	0.00006

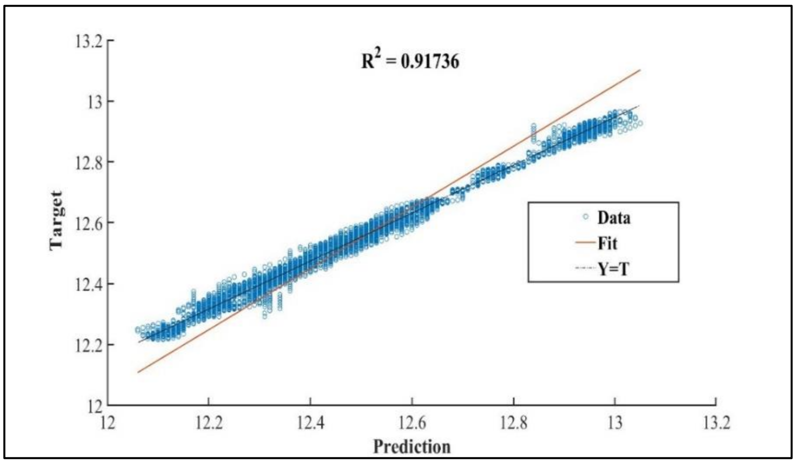

Figure 5. Regression of training dataset.

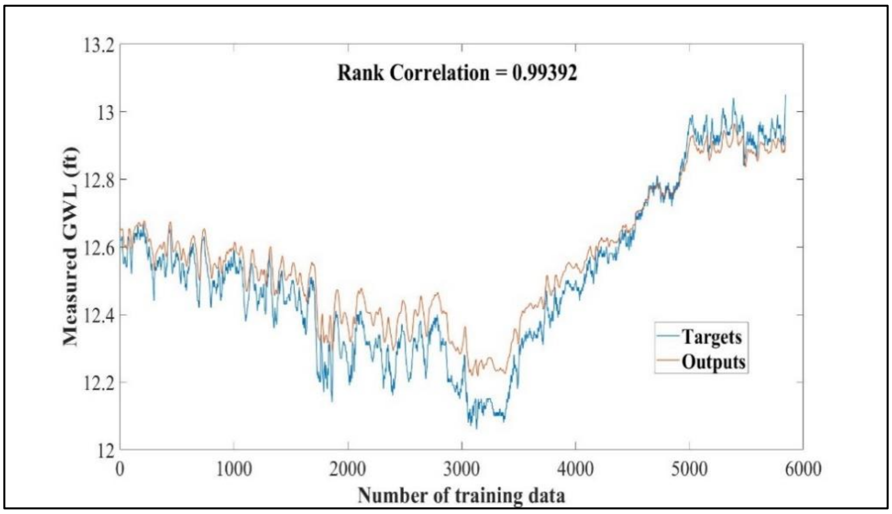

Figure 6. Rank correlation of training dataset.

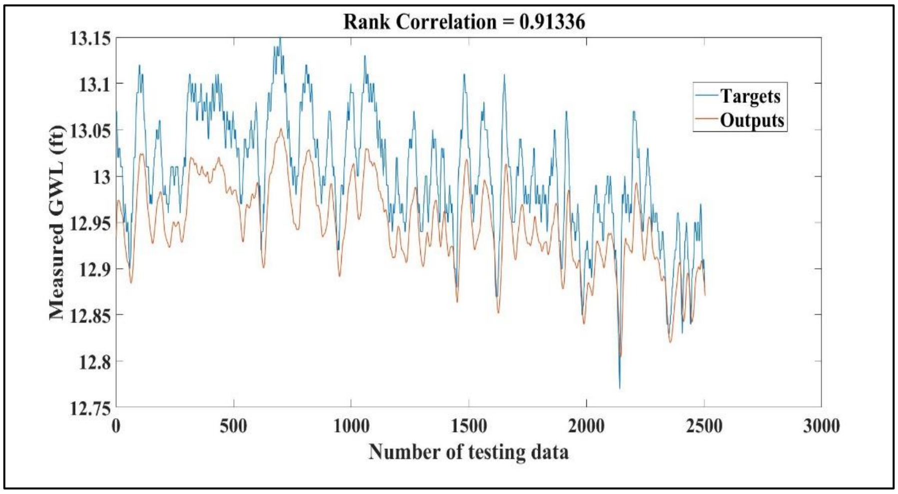

Figure 7. Rank correlation of test dataset.

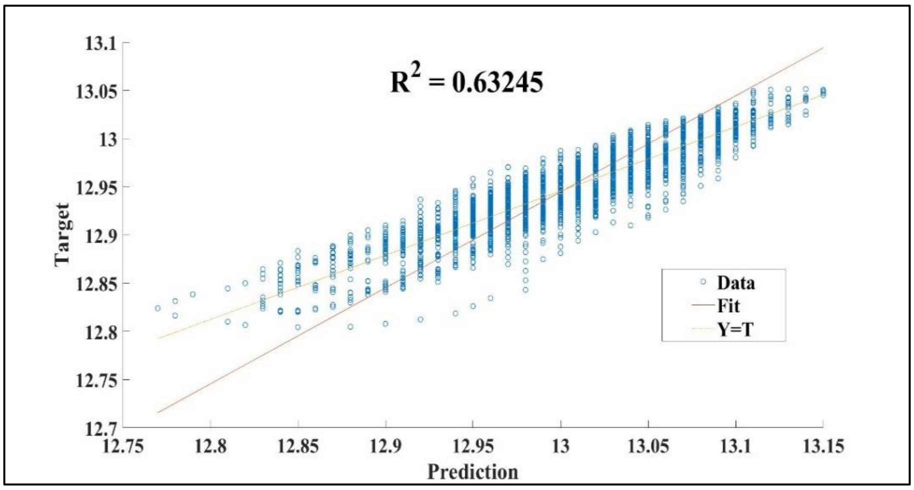

Figure 8. Regression of test dataset.

5. Conclusion

The groundwater level is an essential element that can be impacted due to environmental variation. For example, research of weather variation presents drops in rainfall and increases in temperature, which increase the possible harshness of water resources shortage [35]. Moreover, Investigation of the groundwater level is necessary for efficient groundwater resources management, and it provides information on the groundwater resources availability. Crucial details about aquifer dynamics are usually entrenched in the continuously documented groundwater time series data like the water level [57]. Hence, we used a hybrid neural network called CNN- Bi LSTM, which combines convolutional neural network layers and bidirectional long-short term memory layers (Bi LSTM) to simulate hourly time series groundwater level

The primary outcomes of this study are as follows:

- The CNN-Bi LSTM has shown acceptable results in the training and testing stages, especially in training with high regression.
- The model has demonstrated exemplary performance with data collected from well affected by pumping, especially in the training stage.
- The Bayesian optimization was used for finding the best model for the simulating, and it reached the best state within 21 hours approximately. This long duration can be attributed to the extensive ranges of optimized variables to determine the best parameters and features.

Still, it is recommended to conduct more research that can improve the outcomes by considering these limitations and suggestions:

- The limitation of this work is that only Adaptive Moment Estimation (Adam) is used to calculate updated learning rate, and it is better to examine the effect of various machine learning optimizers.
- The Bayesian optimization was used to find the best parameters like layers or initial learning rates. Still, the model can be optimized using various approaches for optimization like particle swarm optimization and genetic algorithm optimization
- The model's performance can be analyzed using multiple percentages of data for training and testing datasets.
- The performance of the CNN- Bi LSTM model can be compared with a simple LSTM neural network and a simple CNN neural network.
- The model is trained with hourly groundwater level data. Therefore, it is recommended to train the model with different time steps data to examine the effect of time steps such as monthly or daily data on the results.
- The groundwater level data was used as raw data. It is recommended to train the AI model with normalized data to investigate the impact of normalization on the accuracy of prediction.

Conflict of Interest Statement

The authors declare no conflict of interest.

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