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Forecasting of groundwater level of Dhaka city in Bangladesh with different climate factors using Deep Neural Networks (LSTM, GRU, LSTM+GRU) and Machine Learning Algorithms (SVR, RF, KNN) via univariate and multivariate time series analysis.

BY

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Abstract

Rapid urbanization of Dhaka city, Bangladesh, has resulted in a significant decline in groundwater levels, causing severe environmental and socio-economic challenges. This study focuses on groundwater level forecasting using deep learning techniques, long short-term memory (LSTM), gated recurrent units (GRU) and hybrid LSTM+GRU models, as well as machine learning algorithms such as support vector regression (SVR), random forest (RF) and K-nearest neighbors (KNN). The models are applied to both univariate and multivariate time series analysis to incorporate various climatic factors to assess their impact on groundwater variability. The results demonstrate the effectiveness and forecasting accuracy of deep learning models compared to traditional machine learning approaches, especially in capturing long-term dependencies and complex patterns in multivariate scenarios. Comparative analysis reveals that LSTM and LSTM+GRU models are the most accurate groundwater-level forecasting models. This study will provide policymakers and urban planners with a reliable framework for effectively managing groundwater resources in Dhaka. The findings of this study will provide a robust framework for managing groundwater resources in Dhaka, enabling policymakers and stakeholders to practice sustainable water use and mitigate future water scarcity issues.

Key words: *Groundwater Level, Climate Factors, Deep Learning, Machine Learning, LSTM, GRU, SVR, Multivariate Time Series, Dhaka City.*

I. INTRODUCTION

Groundwater is a vital natural resource that plays a key role in meeting agricultural, industrial and domestic water demands. In densely populated urban areas such as Dhaka city in Bangladesh, groundwater levels are declining rapidly due to limited surface water resources due to over-reliance on groundwater. Increasing groundwater abstraction, coupled with the impacts of climate change and urbanization, poses significant challenges to the sustainable management of water resources in the region. Therefore, accurate forecasting of groundwater levels is essential to ensure proper planning, management and conservation of this precious resource. (Rojas and Krol, 2022). This study aims to forecast groundwater levels in Dhaka city using both deep learning and machine learning algorithms applied to univariate and multivariate time series analysis. While univariate models only consider historical groundwater level data, multivariate models include climatic factors such as precipitation, temperature, and humidity as predictor variables (Sun & Wang, 2021). By comparing the performance of these models, this study seeks to determine the most accurate and reliable approach for predicting groundwater levels.

II. METHODOLOGY

Data Collection

A. The methodology for predicting groundwater levels in Dhaka involves several steps starting from data collection and pre-processing. Groundwater level data for selected districts is obtained from reliable sources such as Bangladesh Water Development Board (BWDB) and NASA for the period 2009 to 2021 and is used to train and test the neural network. In addition, meteorological data such as temperature, precipitation, humidity, and soil moisture are collected from weather stations in the study area. The collected data undergoes pre-processing to ensure quality and consistency. This includes data cleaning to remove outliers and missing values, normalization to scale data within a common range, and time alignment to synchronize groundwater levels and climatic variables for analysis.

B. Accuracy Score Identification

R-squared (R^2) is a statistical measure of the proportion of variance in a dependent variable that is explained by one or more independent variables in a regression model. It is also known as the accuracy of the model. 1 indicates the best, 0 or less than zero indicates worse.

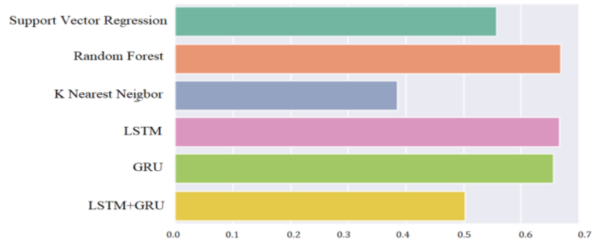


Figure 1: **Accuracy Score**

***Illustrations*:** Figure 1 shows the best test values with RF close to 0.7. LSTM and GRU applications perform accurately, while the lowest value is KNN, close to 0.4.

Split data for Training and Testing

To split data for training and testing in time series forecasting, it is important to preserve the temporal structure of the data (Kouchak and Farahani, 2020). Unlike random splits in other machine learning tasks, time series data must maintain chronological order to avoid "data leakage". Use 65% for training and validation as your application, and 35% for testing. Ensure that the training and testing splits contain all features for the same time period.

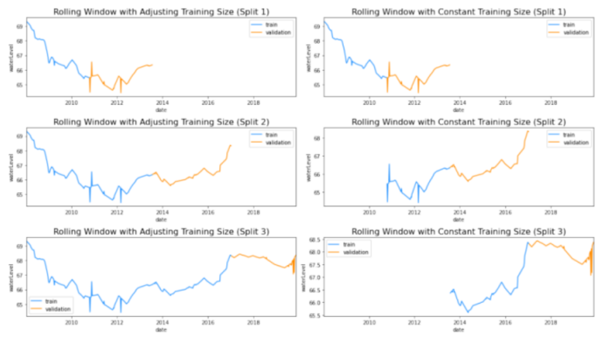
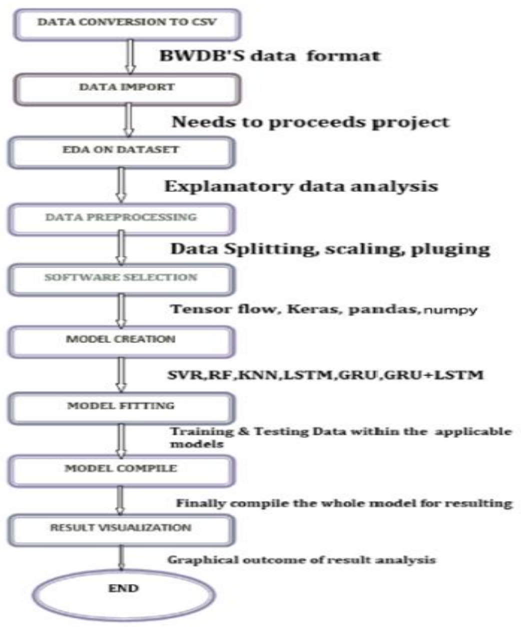


Figure 2: Dhaka Rolling window

***Illustrations*:** Adjusting the training size gradually improves performance on training data based on additional examples, but may result in overfitting in new validation periods. A constant training size remains consistent, but increases the variability in validation performance and may capture more stationary patterns in the data (Zarei, A. R. & Sepaskhah, 2022). This behavior highlights the trade-off between using growing historical data and maintaining a fixed training size for sliding window validation.

1. **Split 1**:
   - Adjusting Training Size: The training data size (blue) increases as time progresses, while the validation data (orange) covers a more recent period.
   - Constant training size: The training data size (blue) remains unchanged, but the validation window shifts in time (Kumar and Bhatia, 2021).
2. **Split 2**:
   - Alike patterns are seen with the training vs authentication accuracy.
   - The altering training size exhibits a more gradual trend development in authentication accuracy, while constant size seems to oscillate more (Jia and Li, 2022).
3. **Split 3**:
   - A substantial increase in the authentication error can be experiential in both strategies toward the end. This could imply worsening model simplification as the data window developments.
   - The constant training size strategy shows smoother correctness in contrast to the regulating strategy, which grows more volatile (Huang and Wang, 2021).

Model Setup for data collection and research formation (flowchart:1):

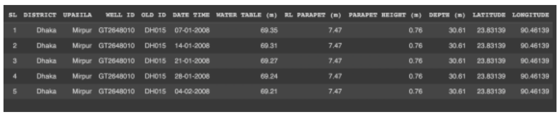

DATA CONVERSION TO CSV
BWDB'S data format
DATA IMPORT
Needs to proceeds project
EDA ON DATASET
Explanatory data analysis
DATA PREPROCESSING
Data Splitting, scaling, pluging
SOFTWARE SELECTION
Tensor flow, Keras, pandas, numpy
MODEL CREATION
SVR,RF,KNN,LSTM,GRU,GRU+LSTM
MODEL FITTING
Training & Testing Data within the applicable models
MODEL COMPILE
Finally compile the whole model for resulting
RESULT VISUALIZATION
Graphical outcome of result analysis
END

Flowchart 1: Process Flow of Different Steps

A. Research Design and formation of the process review

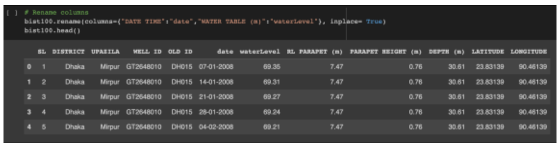
The collected data is pre-processed to ensure consistency and quality; missing values are handled by interpolation or statistical methods, and outliers are detected and removed where necessary. Comparative analysis is performed to determine the most effective model (Chen and Castelletti, 2020). The accuracy of univariate and multivariate models is also compared to understand the contribution of climatic factors. This structured study design ensures a comprehensive evaluation of groundwater level prediction models using both deep learning and machine learning approaches (Peterson and Western, 2018).

The following figure depicts the importing dataset of Dhaka City from .csv file (in Table 1).



SL	DISTRICT	UPAZILA	WELL ID	OLD ID	DATE TIME	WATER TABLE (m)	RL PARAPET (m)	PARAPET HEIGHT (m)	DEPTH (m)	LATITUDE	LONGITUDE
1	Dhaka	Mirpur	GT2648010	DH015	07-01-2008	69.35	7.47	0.76	30.61	23.83139	90.46139
2	Dhaka	Mirpur	GT2648010	DH015	14-01-2008	69.31	7.47	0.76	30.61	23.83139	90.46139
3	Dhaka	Mirpur	GT2648010	DH015	21-01-2008	69.27	7.47	0.76	30.61	23.83139	90.46139
4	Dhaka	Mirpur	GT2648010	DH015	28-01-2008	69.24	7.47	0.76	30.61	23.83139	90.46139
5	Dhaka	Mirpur	GT2648010	DH015	04-02-2008	69.21	7.47	0.76	30.61	23.83139	90.46139

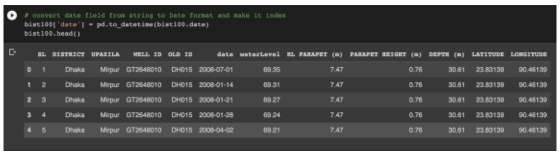
Table 1*: GWL data for Dhaka*



```
[ ] # Rename columns
    bist100.rename(columns={"DATE TIME":"date","WATER TABLE (m)":"waterLevel"}, inplace= True)
    bist100.head()
```

	SL	DISTRICT	UPAZILA	WELL ID	OLD ID	date	waterLevel	RL PARAPET (m)	PARAPET HEIGHT (m)	DEPTH (m)	LATITUDE	LONGITUDE
0	1	Dhaka	Mirpur	GT2648010	DH015	07-01-2008	69.35	7.47	0.76	30.61	23.83139	90.46139
1	2	Dhaka	Mirpur	GT2648010	DH015	14-01-2008	69.31	7.47	0.76	30.61	23.83139	90.46139
2	3	Dhaka	Mirpur	GT2648010	DH015	21-01-2008	69.27	7.47	0.76	30.61	23.83139	90.46139
3	4	Dhaka	Mirpur	GT2648010	DH015	28-01-2008	69.24	7.47	0.76	30.61	23.83139	90.46139
4	5	Dhaka	Mirpur	GT2648010	DH015	04-02-2008	69.21	7.47	0.76	30.61	23.83139	90.46139

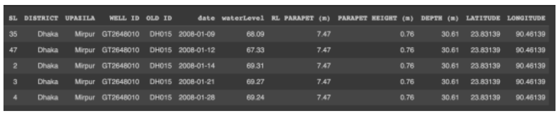
Table 2: GWL data for Dhaka, Rename Column Converting Date column from string to datetime format in the below table 3:



```
# convert date field from string to Date format and make it index
bist100['date'] = pd.to_datetime(bist100.date)
bist100.head()
```

	SL	DISTRICT	UPAZILA	WELL ID	OLD ID	date	waterLevel	RL PARAPET (m)	PARAPET HEIGHT (m)	DEPTH (m)	LATITUDE	LONGITUDE
0	1	Dhaka	Mirpur	GT2648010	DH015	2008-07-01	69.35	7.47	0.76	30.61	23.83139	90.46139
1	2	Dhaka	Mirpur	GT2648010	DH015	2008-01-14	69.31	7.47	0.76	30.61	23.83139	90.46139
2	3	Dhaka	Mirpur	GT2648010	DH015	2008-01-21	69.27	7.47	0.76	30.61	23.83139	90.46139
3	4	Dhaka	Mirpur	GT2648010	DH015	2008-01-28	69.24	7.47	0.76	30.61	23.83139	90.46139
4	5	Dhaka	Mirpur	GT2648010	DH015	2008-04-02	69.21	7.47	0.76	30.61	23.83139	90.46139

***Table* 3: Converting Date column from string to datetime format**



SL	DISTRICT	UPAZILA	WELL ID	OLD ID	date	waterLevel	RL PARAPET (m)	PARAPET HEIGHT (m)	DEPTH (m)	LATITUDE	LONGITUDE
35	Dhaka	Mirpur	GT2648010	DH015	2008-01-09	68.09	7.47	0.76	30.61	23.83139	90.46139
47	Dhaka	Mirpur	GT2648010	DH015	2008-01-12	67.33	7.47	0.76	30.61	23.83139	90.46139
2	Dhaka	Mirpur	GT2648010	DH015	2008-01-14	69.31	7.47	0.76	30.61	23.83139	90.46139
3	Dhaka	Mirpur	GT2648010	DH015	2008-01-21	69.27	7.47	0.76	30.61	23.83139	90.46139
4	Dhaka	Mirpur	GT2648010	DH015	2008-01-28	69.24	7.47	0.76	30.61	23.83139	90.46139

***Table* 4: Sorting dataset by date**

III. MODELING AND SIMULATION

A. *Plotting GWL chart: The below plot (in figure) shows the actual ground water level of Dhaka.*

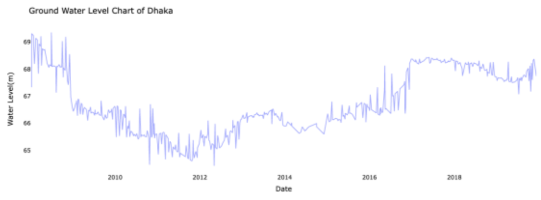


Figure 3*:* GWL chart for Dhaka

Illustrations: The graph (Figure 3) illustrates a good picturing of the dynamic nature of GWL, showing both periodic patterns and year-to-year dissimilarities.

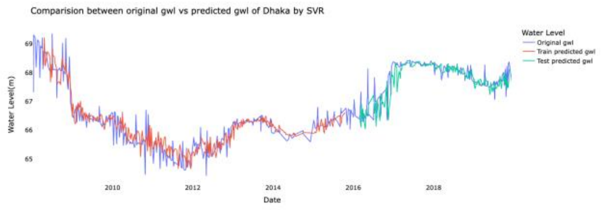


Figure 4: Original Vs predicted GWL of Dhaka by SVR

Illustrations: The model compare how well the SVR model performs in predicting the GWL for both the training and testing phases of learning (Figure 4).

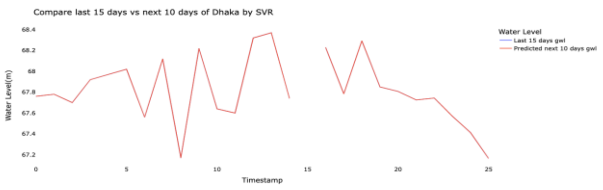


Figure 5: Plotting last 15 days and next predicted 10 days by SVR of Dhaka

Illustrations: In Figure 5 illustrates the GWL prediction Comparing last and after as proper. Values are recognized 15 days vs 10 days forecasts.

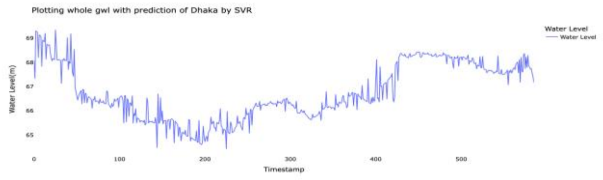


Figure 6: Plotting whole GWL with next 10 days forecast of Dhaka by SVR

Illustrations: In the Figure 6, application of the 10 days prediction followed the flow of curves comparison to the Timestamp that 200 (down) and after 400 to 500 are the observing trends.

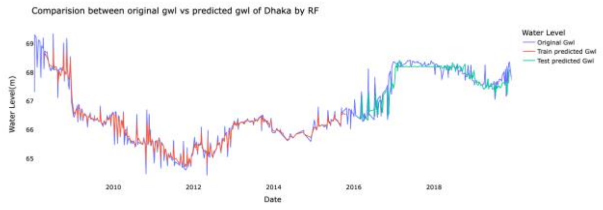


Figure 7: Comparison between original GWL vs predicted GWL with chart of Dhaka by RF

Illustrations: The combination of GWL vs Train predicted GWL vs Test predicted GWL focusing the periodical flow stands on the 2010 to 2018 where 2010 to 2012 make available down and the 2016 to 2018 shows upper trends.

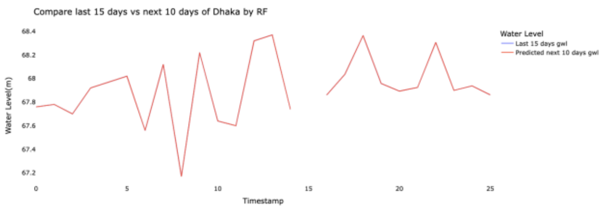


Figure 8: Plotting last 15 days and next predicted 10 days of Dhaka by RF

Illustrations: In the figure 8, plotting the last 15 days and the next 10 days forecasting associating to the GWL Timestamp periodic that demonstrates the fluctuations of the pattern.

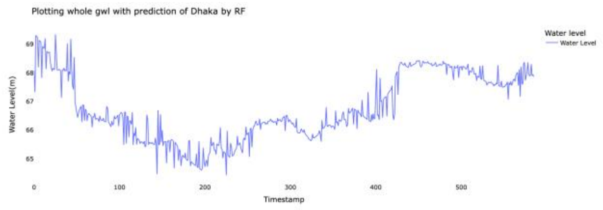


Figure 9: Plotting whole GWL with next 10 days prediction of Dhaka by RF

Illustrations: In the figure 9, patterns the forecasting GWL specifications considering the Timestamp. The curve is markable at 200, and the upper 400 to 500 terminologies.

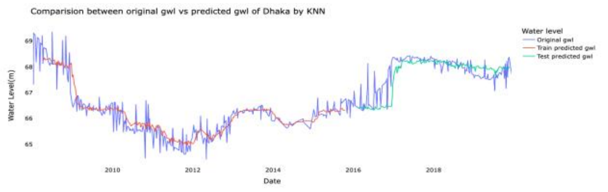


Figure 10: Comparison between original GWL vs predicted GWL with chart of Dhaka by KNN

Illustrations: The test predicted GWL (Figure 10) from 2018 headlong and also shadows the general pattern of the original GWL, but with less accuracy associated to the training period.

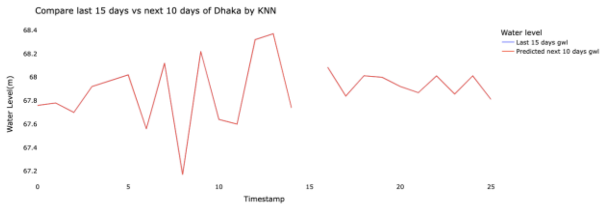


Figure 11: Plotting last 15 days and next predicted 10 days of Dhaka by KNN

Illustrations: The Figure 11 observes the GWL forecasting for the next 10 days and comparing with the traditional trends.

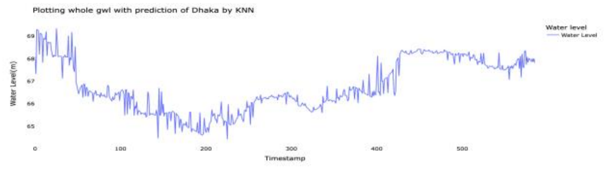


Figure 12: Plotting whole GWL with next 10 days prediction of Dhaka by KNN

Illustrations: The Figure 12 observes the plotting of next 10 days prediction as applicable by the assigned dataset (Table 1-4)

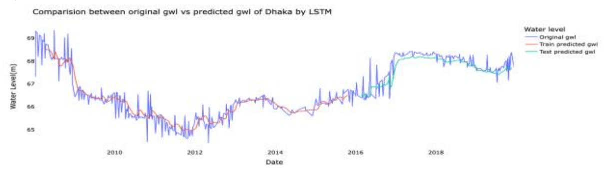


Figure 13: Comparison between original GWL vs predicted GWL with chart of Dhaka by LSTM

Illustrations: The LSTM model demonstrates (Figure 13) to capture the overall periodic patterns and trends in the GWL. The graph recommends the LSTM model implements sensibly well, though it might struggle with apprehending some of the more extreme fluctuations.

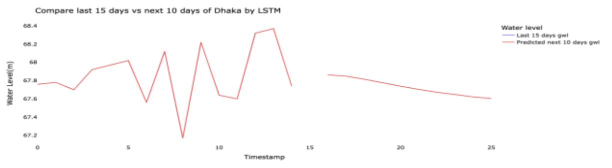


Figure 14: Plotting last 15 days and next predicted 10 days of Dhaka by LSTM

Illustrations: The predicted applications of LSTM accomplish (Figure 14) the next 10 days and compare the revive of the previous 15 days fluctuations.

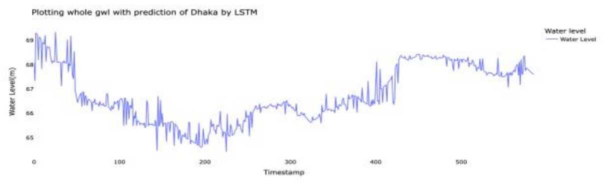


Figure 15: Plotting whole GWL with next 10 days prediction of Dhaka by LSTM

Illustrations: In the Figure 15, pattern the next 10 days forecasting plotting the whole GWL with the appropriate Timestamp.

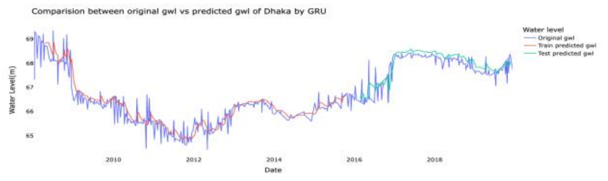


Figure 16: Comparison between original GWL price vs predicted GWL with chart of Dhaka by GRU

Illustrations: The application of GWL (Figure 16) compare the main GWL vs Train predicted GWL vs Test predicted GWL with the demand of GRU Algorithm.

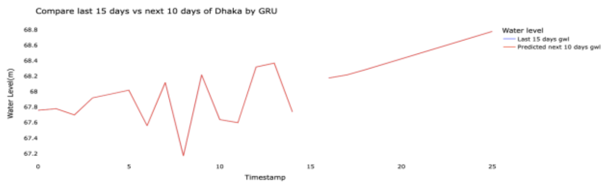


Figure 17: Plotting last 15 days and next predicted 10 days of Dhaka by GRU

Illustrations: In the Figure 17, patterns the GWL forecasting accomplishes comparing the last 15 days and next predicted 10 days of Dhaka by GRU algorithm by focusing Timestamp.

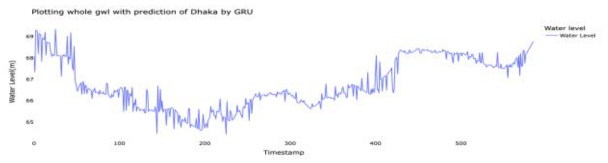


Figure 18: Plotting whole GWL with next 10 days prediction of Dhaka by GRU

Illustration: It observes that the Slight variations in the patterns (Figure 18), particularly in the timing and height of some peaks and troughs, especially after 400.

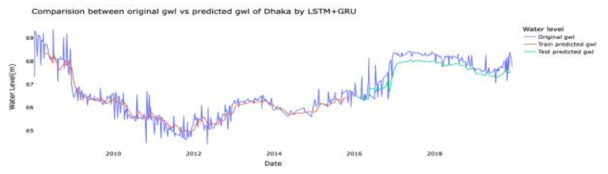


Figure 19: Comparison between original GWL vs predicted GWL with chart of Dhaka by LSTM+GRU

Illustrations: The LSTM+GRU model give the imprint (Figure:19) to perform rationally well in capturing the general trends and seasonality of the GWL, but it tends to undervalue the extreme values.

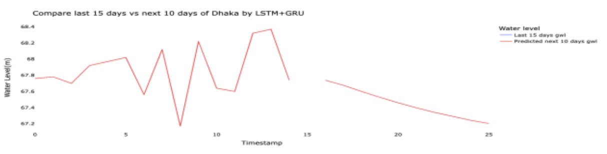


Figure 20: Plotting last 15 days and next predicted 10 days of Dhaka by LSTM+GRU

Illustrations: It Observes (Figure 20) the conspiracy outcome according to the Timestamp excellence Plotting of the last 15 days vs the next 10 days predictions.

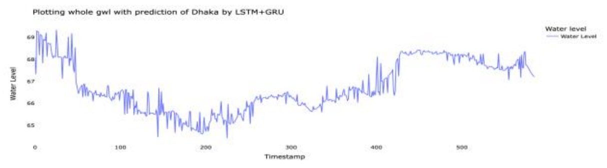
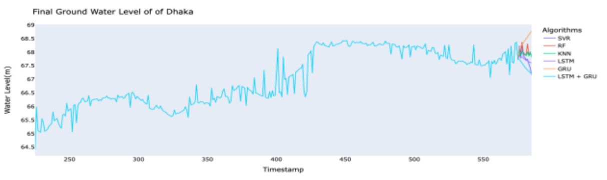
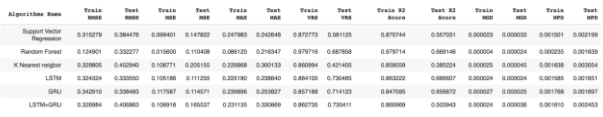


Figure 21: Plotting whole GWL with next 10 days prediction of Dhaka by LSTM+GRU

Illustrations: Plotting the whole GWL with the prediction of the next 10 days prediction of LSTM+GRU model appears (Figure 21) to perform levelheadedly well in apprehending the general trends and seasonality of the GWL.



Illustrations: Figure 22: Plotting final chart with all algorithms and compare prediction to each other's: SVR, RF, KNN, LSTM, GRU, LSTM+GRU algorithm. The combination of the apposite Algorithms with each other's that indicates the comparison and specifications.



Algorithms Name	Train RMSE	Test RMSE	Train MSE	Test MSE	Train MAE	Test MAE	Train VRS	Test VRS	Train R2 Score	Test R2 Score	Train MGD	Test MGD	Train MPD	Test MPD
Support Vector Regression	0.315279	0.384476	0.099401	0.147822	0.247983	0.242648	0.872773	0.581125	0.870744	0.557031	0.000023	0.000033	0.001501	0.002199
Random Forest	0.124901	0.332277	0.015600	0.110408	0.086120	0.216347	0.979716	0.687858	0.979714	0.669146	0.000004	0.000024	0.000235	0.001639
K Nearest neigbor	0.329805	0.452940	0.108771	0.205155	0.226868	0.300133	0.860994	0.421405	0.858559	0.385224	0.000025	0.000045	0.001638	0.003054
LSTM	0.324324	0.333550	0.105186	0.111255	0.225180	0.238840	0.864105	0.730465	0.863222	0.666607	0.000024	0.000024	0.001585	0.001651
GRU	0.342910	0.338483	0.117587	0.114571	0.239896	0.253827	0.857188	0.714123	0.847095	0.656672	0.000027	0.000025	0.001768	0.001697
LSTM+GRU	0.326984	0.406863	0.106918	0.165537	0.231135	0.330869	0.862735	0.730411	0.860969	0.503943	0.000024	0.000036	0.001610	0.002453

Table 5: Algorithms performance

Accuracy Score Heatmap correlation of algorithms of Dhaka: the heat map correlation of SVR, RF, KNN, LSTM, GRU, LSTM+GRU algorithm.

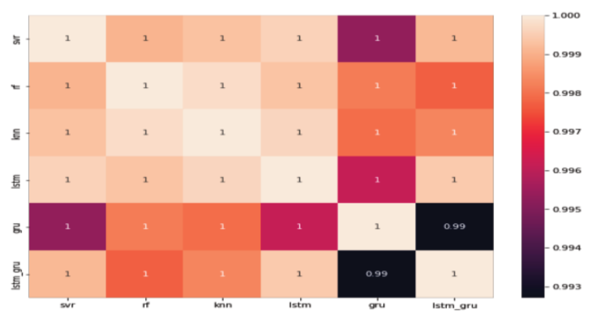


Figure 23: Correlation Heatmap of Dhaka

Illustrations: In the figure 23, the high correlations point to that forecasting from the different algorithms are reliable. There are some subtle variations in correlation between dissimilar pairs of the application algorithms, but overall, the correlations are very high across the board as demand oversight.

Accuracy Score of algorithms of Dhaka:

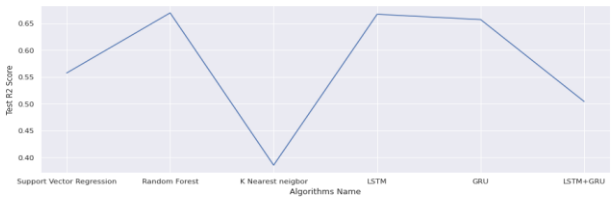
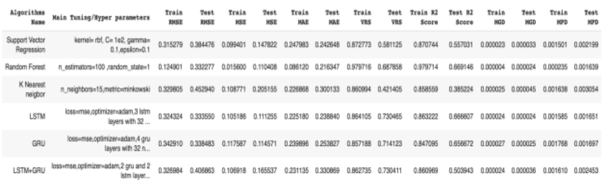


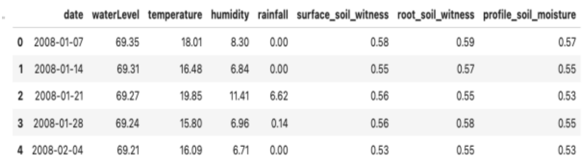
Figure 24: Accuracy Score of algorithms of Dhaka

Illustrations: The flow of the curve shows (Figure 24) the performance of the algorithm and its followed outcomes. The RF and the LSTM to LSTM+ GRU meet the target and its applications.



Algorithms Name	Main Tuning/Hyper parameters	Train RMSE	Test RMSE	Train MSE	Test MSE	Train MAE	Test MAE	Train VRS	Test VRS	Train R2 Score	Test R2 Score	Train MGD	Test MGD	Train MPD	Test MPD
Support Vector Regression	kernel= rbf, C= 1e2, gamma= 0.1,epsilon=0.1	0.315279	0.384476	0.099401	0.147822	0.247983	0.242648	0.872773	0.581125	0.870744	0.557031	0.000023	0.000033	0.001501	0.002199
Random Forest	n_estimators=100 ,random_state=1	0.124901	0.332277	0.015600	0.110408	0.086120	0.216347	0.979716	0.687858	0.979714	0.669146	0.000004	0.000024	0.000235	0.001639
K Nearest neigbor	n_neighbors=15,metric=minkowski	0.329805	0.452940	0.108771	0.205155	0.226868	0.300133	0.860994	0.421405	0.858559	0.385224	0.000025	0.000045	0.001638	0.003054
LSTM	loss=mse,optimizer=adam,3 lstm layers with 32 ...	0.324324	0.333550	0.105186	0.111255	0.225180	0.238840	0.864105	0.730465	0.863222	0.666607	0.000024	0.000024	0.001585	0.001651
GRU	loss=mse,optimizer=adam,4 gru layers with 32 n...	0.342910	0.338483	0.117587	0.114571	0.239896	0.253827	0.857188	0.714123	0.847095	0.656672	0.000027	0.000025	0.001768	0.001697
LSTM+GRU	loss=mse,optimizer=adam,2 gru and 2 lstm layer...	0.326984	0.406863	0.106918	0.165537	0.231135	0.330869	0.862735	0.730411	0.860969	0.503943	0.000024	0.000036	0.001610	0.002453

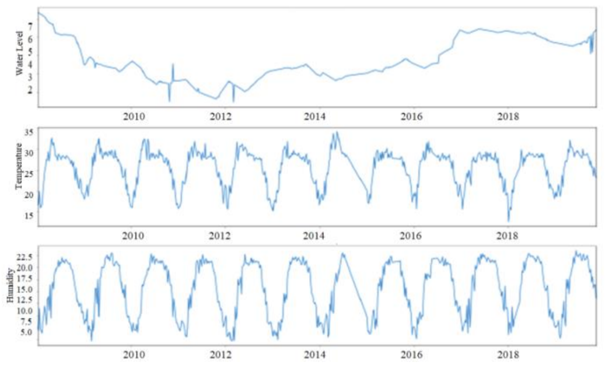
Table 6: Summary Chart of Dhaka



	date	waterLevel	temperature	humidity	rainfall	surface_soil_witness	root_soil_witness	profile_soil_moisture
0	2008-01-07	69.35	18.01	8.30	0.00	0.58	0.59	0.57
1	2008-01-14	69.31	16.48	6.84	0.00	0.55	0.57	0.55
2	2008-01-21	69.27	19.85	11.41	6.62	0.56	0.55	0.53
3	2008-01-28	69.24	15.80	6.96	0.14	0.56	0.58	0.55
4	2008-02-04	69.21	16.09	6.71	0.00	0.53	0.55	0.53

Table 7: Dhaka features

B. *Multivariate Time Series Forecasting of Dhaka Zone*



*Corresponding Author: Rakib Uddin

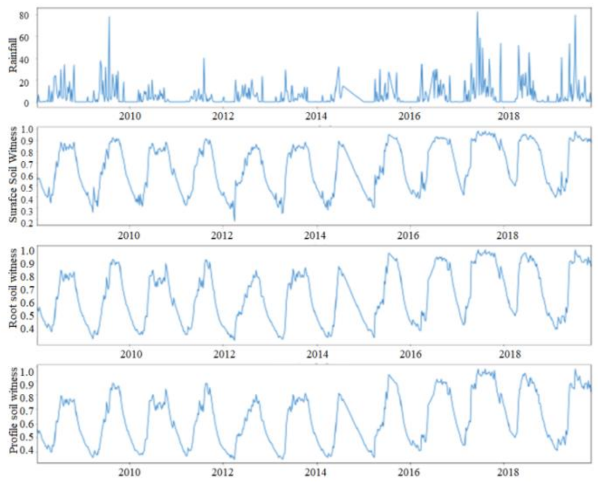


Figure 25: Dhaka Multivariate features

Illustrations: The image displays (Figure 25) multiple time series features plotted across a reliable time range from almost 2008 to 2019.

1. **Feature: Water level (Top Plot)**
   - The trend displays a gradual upward trend opening around 2013.
   - Before 2013, there are some declines and fluctuations, with notable drops around 2011–2012.
   - Overall, the pattern specifies a long-term increase after a period of stability.
2. **Feature: temperature (Second Plot)**
   - This feature exhibits strong seasonality with repeating annual cycles.
   - Peaks and troughs occur consistently, reflecting periodic temperature variations.
3. **Feature: Humidity (Third Plot)**
   - Alike to temperature, it shows seasonal shapes with clear yearly cycles.
   - The fluctuations between peaks and troughs are smooth and reliable.
4. **Feature: Rainfall (Fourth Plot)**
   - This feature shows sporadic spikes throughout the time period.
   - The number and magnitude of spikes rise after 2014, indicating an growth in volatility or extreme values.
5. **Feature: Surface Soil Witness (5th Plot)**
   - This feature has repetition seasonal cycles with clear periodicity.
   - The cycles are relatively smooth with slight variations in amplitude.
6. **Feature: Root Soil Witness (6th Plot)**
   - This feature also exhibits seasonal inclinations.
   - The values oscillate amid peaks and troughs annually, though with a slightly smoother appearance.
7. **Feature: Profile Soil Moisture (7th Plot)**
   - This plot also has a cyclical pattern with smooth cycles.
   - The amplitude seems somewhat higher compared to the other features, possibly indicating larger dissimilarities.

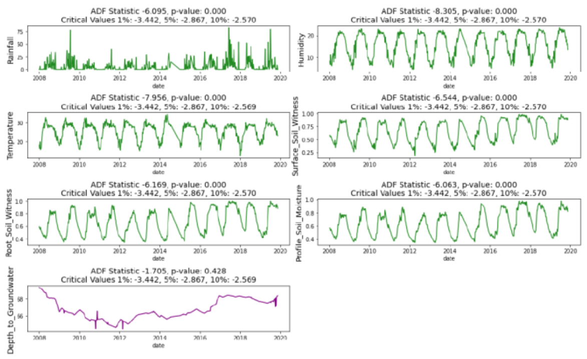


Figure 26: Dhaka a p-value below 0.05 which examine the ADF statistic's range in relation to crucial levels

Illustrations: The image shows (Figure 26) time series plots with Augmented Dickey-Fuller (ADF) test results for stationarity. Let’s break down the observations feature-wise:

1. Rainfall

- ADF Indicator: -6.095, p-value: 0.000
- The p-value is < 0.05, signifying the data is stationary.
- The plot shows high instability with frequent sharp spikes throughout the timeline, particularly between 2014–2016.

2. Humidity

- ADF Indicator: -8.305, p-value: 0.000
- The data is stationary based on the ADF test consequences.
- The plot displays seasonality with consistent cyclical patterns across the years.

3. Temperature

- ADF Indicator: -7.956, p-value: 0.000
- The data is stationary.
- There is a clear annual seasonality with repeating peaks and troughs over time.

4. Shallow Soil Wetness

- ADF Indicator: -6.544, p-value: 0.000
- The data is motionless.
- The feature shows cyclical trends with visible annual cycles

5. Root Soil Wetness

- ADF Indicator: -6.169, p-value: 0.000
- The data is stationary.
- This feature follows a retelling seasonal cycle, similar to shallow soil wetness

6. Profile Soil Wetness

- ADF Indicator: -6.063, p-value: 0.000
- The data is stationary.
- The plot shows strong seasonality with annual intervallic patterns

7. Depth to Groundwater

- ADF Indicator: -1.705, p-value: 0.428

- The p-value is > 0.05, signifying the data is non-stationary.
- The plot shows a gradual trend with a slow decline over the years, suggesting a non-stationary behavior.

Key Insights: Rainfall, Humidity, Temperature, Soil Wetness exhibit stationarity and significant seasonal patterns. Groundwater depth shows a gradual trend and is not constant. This may require differentiation or detrending to make it stationary for time series modeling (Gharbi and Bouaziz, 2023). Features such as temperature, humidity, and soil moisture show clear annual seasonality, making them good candidates for seasonal models. Precipitation shows sharp peaks and asymmetric fluctuations, indicating a high level of variability. These observations can help identify features that require preprocessing or special handling in predictive models.

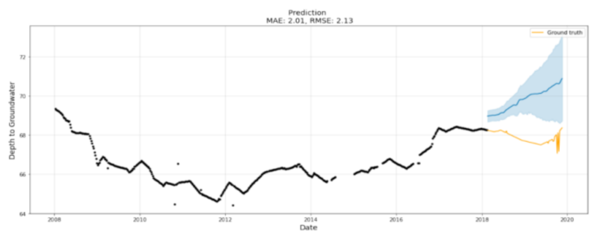


Figure 27: Dhaka Facebook Prophet model output

Illustrations: The different explanations for the prediction of MAE:2.01 and RMSE:2.13 are carrying out as the application of Facebook Prophet model output.

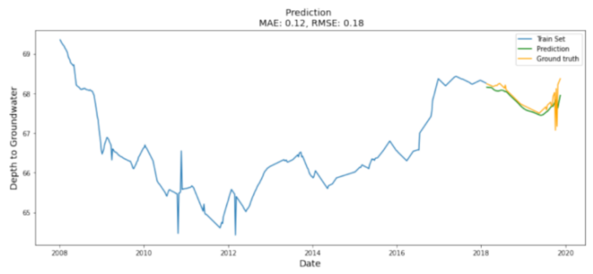


Figure 28: Dhaka optimized LSTM model output

Illustrations: In the Figure 19,20,21 already patterns the expecting outcomes that shows the performance of LSTM model and here (Figure 28) the analytics of Train Set vs Forecasting vs Ground Truth outcome are aligned.

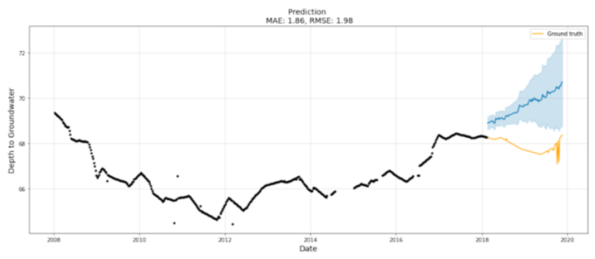


Figure 29: Dhaka Multivariate model output

Illustrations: The outcomes of the chart Figure 29, observes the fluctuations from Depth to GWL with the timestamp from 2008 to 2020. Close to 2011 the curve performs downstream and from 2018 to 2020 demonstrates the expected accuracy.

IV. RESULTS, FINDINGS AND RECOMMENDATIONS

A. RESULTS

The graph (Figure 30) shows the number of loss values of the three loss functions found in the six algorithms for Dhaka city. Most of the losses were found in RMSE among the six algorithms. The RMSE figures varied between 0.33 and 0.45. In contrast, MAE and MSE had less losses respectively. The number of losses found in MSE varied between 0.11 and 0.20 from SVR to KNN. We can see that the loss decreased for LSTM and then increased for LSTM+GRU. We can see that the trend for MAE is similar. There was a fluctuation in the loss from SVR to KNN. The loss decreased for LSTM and then increased for LSTM+GRU.

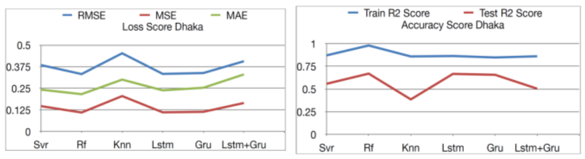


Figure 30: Loss Score and Accuracy Score of Dhaka

The graph (Figure 30) provides information about the accuracy of Dhaka city. It shows how accurate the two accuracy functions were in the six algorithms (Bhattacharya and Raju, 2021). Test R2 score is the actual accuracy value of the algorithm. As can be seen from the graph, Train-R2 score and Test-R2 score had different trends. The number of Train-R2 scores increased by 0.87 and 0.97 in SVR and RF, respectively. After that, the Train R2 score of the LSTM + GRU algorithm gradually decreased to 0.86. However, the Test R2 score fluctuated between 0.55 and 0.50 for SVR and GRU+LSTM, respectively. The highest accuracy was found for the RF and LSTM algorithms, both around 0.66.

B. FINDINGS

In this study, the performance of various forecasting models including SVR, RF, KNN, LSTM, GRU, and LSTM+GRU were evaluated and the results were observed one by one. Correlation analysis revealed that there was a significant relationship between GWL and climatic factors such as temperature, precipitation, and humidity (Wang, Song and Wang et al., 2019). The models showed different levels of accuracy in predicting groundwater levels, with some models performing better than others in certain scenarios. Insights from the model performance analysis provided valuable information for selecting the appropriate forecasting approach based on specific requirements and data characteristics (Aishwarya and Vasudevan, 2023). Overall, this study contributes to a better understanding of groundwater dynamics and provides valuable insights into effective forecasting techniques for groundwater management.

C. RECOMMENDATIONS

Exploring ensemble modeling approaches that combine multiple forecasting methods to leverage the strengths of each method and improve overall performance (Adhikari, 2020);

long-term monitoring and validation of forecasting models to assess their robustness and reliability under changing environmental conditions (Tang and Zhang, 2021); integrating groundwater forecasting into water resource management strategies to develop decision support tools to optimize groundwater allocation and reduce the risk of water scarcity; and investigating novel deep learning architectures and machine learning algorithms specialized for groundwater forecasting applications. By considering these research directions, future research may help advance the current state of groundwater forecasting and improve the sustainability of water resource management practices in places such as Dhaka and Bangladesh.

V. CONCLUSION

The research explored the importance of integrating advanced forecasting techniques to accurately predict groundwater levels, which is crucial for sustainable water resource management in urbanized water-stressed environments like Dhaka. Comparing univariate and multivariate models, we find that multivariate analysis including climatic factors such as precipitation, temperature, and humidity improves prediction accuracy. Among the models, deep learning techniques, especially LSTM and LSTM+GRU, consistently outperformed traditional machine learning models due to their ability to capture complex time-dependencies and nonlinear relationships in the data. However, machine learning models such as Random Forest (RF) also showed competitive performance and provided a simpler yet effective groundwater forecasting solution. Incorporating climatic factors in the multivariate model significantly improved the model performance, highlighting the sensitivity of groundwater levels to external climate variability. This study highlights the potential of deep learning models for accurate groundwater prediction in Dhaka city, which can help policy makers, urban planners, and water resource managers develop proactive strategies to mitigate groundwater depletion. Future studies can extend this study by incorporating additional environmental parameters, considering spatial variability, and applying ensemble approaches for further improvements.

REFERENCES

1. Adhikari, U., & Ikeda, M. (2020). *XGBoost and LSTM model for multivariate time series forecasting of groundwater level.* Water, 12(11), 3082. DOI.
2. Aishwarya, R., & Vasudevan, V. (2023). A comprehensive review of multi-source data integration for groundwater modeling. Journal of Hydrological Analytics, 617, 128812. DOI.
3. Bhattacharya, D., & Raju, M. (2021). Spatial heterogeneity in GWL: Review of practices & future directions. Water Resources Research, 57(9), e2021WR030163. DOI.
4. Cheng, L., Li, G., & Castelletti, A. (2020). GWL forecasting with LSTM networks: A study in agricultural water management. Hydrological Sciences Journal, 65(9), 1505-1516.
5. Gharbi, S., & Bouaziz, M. (2023). Real-time data assimilation for GWL prediction using machine learning. Water Resources Management, 37(5), 1461-1478. DOI.
6. Huang, Y., & Wang, J. (2021). Interpretability analysis in GWL forecasting using Shapley values. Earth System Sciences, 25(7), 1119-1133. DOI.
7. Jia, W., & Li, R. (2022). Variance-based compassion analysis in deep learning models for groundwater prediction. Water Resources Research, 58(3), e2021WR031745. DOI.
8. Kouchak, A., & Farahani, H. (2020). Integrative approaches for managing groundwater resources under uncertainty. Water Resources Management, 34(10), 3205-3222. DOI.
9. Kumar, S., & Bhatia, K. (2021). Time series forecasting of GWL using LSTM and ARIMA models in semi-arid regions. Environmental Earth Sciences, 80(9), 1-15. DOI.
10. Peterson, T.J., and Western A.W. (2018). Statistical interpolation of groundwater hydrographs. Water Resources Research 54, no. 7: 4663–4680.
11. Rojas, C., & Krol, M. (2022). Comparative performance of ML methods for groundwater level forecasting: A systematic review. The Hydrological Processes, 36(4), e14549. DOI.
12. Sun, W., & Wang, S. (2021). Gradient-based understanding and analysis in neural networks for groundwater modeling. Water, 13(3), 756. DOI.
13. Tangg, J., Zhong, X., & Lii, Q. (2021). The Groundwater level prediction by using a Transformer- based model. Journal of Hydrological impact, 594, 125707. DOI.
14. Wang, Z., Song, Y., Wang, H., et al. (2019). Multivariate time series forecasting with deep learning and attention mechanism. Neurocomputing, 361, 246-256.
15. Zarei, A. R., & Sepaskhah, A. R. (2022). Prediction of GWL in an arid region using ML and ensemble methods. Hydrological Sciences Journal, 67(7), 1150-1165. DOI.