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Modelling and Simulation of Univariate Model of 'Groundwater' and Multivariate Model of 'Rainfall, Temperature, Root and Topsoil, Depth to Groundwater Table' Using Deep Learning and Machine Learning Analysis for Time Series Forecasting of Neural Network Model in Rajshahi Region of Bangladesh

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Abstract: This study investigates modeling and simulation of groundwater dynamics using univariate and multivariate time series forecasting. While the univariate analysis focuses on the water table, the multivariate analysis integrates relevant variables such as precipitation, temperature, root and surface soil cover, and depth to the water table. The incorporation of advanced computational systems such as deep learning and machine learning significantly improves the analytical accuracy and model robustness compared to traditional numerical approaches. The main outcomes of this study include an extension of the projection model that can estimate groundwater levels based on existing historical data of relevant variable quantities. The developed model can help policymakers and stakeholders make informed decisions regarding groundwater utilization and conservation.

Keywords: Univariate, Multivariate, Temperature, Humidity, Rainfall, Surface Soil Witness, Time Series, Rajshahi, Bangladesh.

I. INTRODUCTION

This study provides a comprehensive overview of how advanced analytical techniques such as deep learning (DL) and machine learning (ML) can be applied to time series forecasting, especially in groundwater management and environmental monitoring. We develop methods to interpret the decision-making process of DL models to better understand the relationships between variables. To improve forecast accuracy, the relationships between multiple climate and environmental factors are modeled together (Adhikari and Ikeda, 2020).

Precipitation modeling and simulation are important tools to account for and predict precipitation patterns. Temperature modeling in particular supports weather forecasting, confirming climate change, and responding to agricultural services. To analyze the above statement, several machine learning algorithms can be used, such as Support Vector Regression (SVR), Random Forest (RF), K-Nearest Neighbors (KNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). The focus of this study was on the current extensions, advances, limitations, and shortcomings of advanced neural networking (ANN) techniques using deep learning systems (Gharbi and Bouaziz, 2023).

Relevant and expected measurement level data was used to train and test the neural network. The predictive accuracy of each network structure was evaluated using performance principles, mean squared error (MSE), root mean squared error (RMSE), and other metrics (R2). The results of time series forecasting by the neural network (NN) model were demonstrated in the Rajshahi region, located at latitude 24.1851 and longitude 88.8397.

II. METHODOLOGY

A. Data Collection

Below is a breakdown of how data collection and modeling can be organized for such a study in the Rajshahi area of Bangladesh.

1) Objective

- Develop univariate models for analyzing and predicting groundwater levels over time.
- Build multivariate models to study the combined effects of:
  - Rainfall
  - Temperature
  - Root and surface soil wetness
  - Depth to groundwater level
- Apply deep learning (DL) and machine learning (ML) models for time series analytics and forecasting.

2) Data Collection

2.1. Data Sources

- Groundwater Level Data: Obtain historical groundwater level records from: Bangladesh Water Development Board - BWDB.
- Rainfall Data: Collect data from: NASA
- Temperature Data: Daily temperature readings from: NASA
- Soil Moisture and Wetness Data: NASA
- Depth to Groundwater Level: NASA, BWDB

2.2. Data Frequency and Resolution

- Collect data at daily, monthly, or seasonal intervals.
- Ensure undeviating frequency for multivariate models

2.3. Data Preprocessing (Simoni, Manoli and G., 2021)

- Handle missing values
- Standardize units and scales across features.
- Address outliers through numerical tests
- Ensure stationarity in time series data were essential

3) Analytical Models

3.1. Univariate Models for Groundwater

- Machine Learning Models:
  - SVR (support vector regression)
  - RF (Random Forest)
  - KNN (K-nearest neighbors)
- Deep Learning Models:
  - LSTM (Long Short-Term Memory)
  - GRU (Gated Recurrent Unit)
  - RNN (Recurrent Neural Networks)

3.2. Multivariate Models for Combined Analytics

- Feature Engineering:
  - Correlation analysis to select significant variables.
  - Use lagged variables to capture temporal effects.
- Machine Learning Models
- Deep Learning Models

4) Time Series Analysis and Performances

4.1. Data Excruciating (Tang, Zhang and Li, 2021)

- Use rolling windows with regulating or constant training sizes
- Split data into:
  - Training set
  - Authentication set for hyperparameter tuning.
  - Test set to assess model performance.

4.2. Feature Scaling (Wang, Song, Wang, H., et al., 2019)

- Apply scaling performances:
  - Min-Max Scaling for features like rainfall and temperature.
  - Standardization for topographies with large variability.

4.3. Performance Metrics (Zarei, Sepaskhah, and A. R., 2022).

- Univariate Models analytics:
  - Mean Absolute Error (MAE).
  - Root Mean Squared Error (RMSE).
  - Mean Absolute Percentage Error (MAPE).
- Multivariate Models:
  - R-squared for goodness-of-fit.
  - Cross-correlation function (CCF) to authenticate feature dealings.

5) Deep Learning Framework

5.1. Frameworks and Tools

- Python Libraries:
  - TensorFlow/Keras for deep learning models.
  - PyTorch for flexibility in custom architectures.
  - Scikit-learn for traditional ML techniques.
- Visualization Tools:
  - Matplotlib and Seaborn for examining data analysis.
  - Plotly for collaborative plots.

5.2. Model Training

- Use early ending to prevent overfitting.
- Optimize hyperparameters by means of tools like grid search.

5.3. Explainability

- Use techniques like SHAP for interpretation of multivariate model forecasts.

6) Applications (Shi, Chen and Wang et.al.,2015)

- Water Resource Supervision:
  - Forecast groundwater levels to plan irrigation schedules.
  - Manage potential water shortages.
- Climate Impact Assessment:
  - Realize how rainfall and temperature trends influence groundwater.
  - Evaluate vulnerability to droughts in the Rajshahi area.
- Agricultural Development:
  - Enhance crop selection and irrigation based on soil moisture and groundwater forecasts.

7) Challenges (Rojas and Krol, 2022)

1. Data Accessibility:
   - Restricted high-resolution and long-term data for some features.
   - Reliance on satellite data for soil wetness may familiarize biases.

2. Model Complexity:
   - Corresponding simplicity and performance, particularly in multivariate models.
3. Stationarity Issues:
   - Multivariate relationships may shift over time, demanding dynamic model updates.
4. Computational Resources:
   - Deep learning models, particularly transformers, require substantial computational power.

This method combines progressive time series modeling performances with domain-specific knowledge to derive actionable perceptions for justifiable water resource managing in the Rajshahi region.

B. Loss and accuracy formations

The analytics of R-squared (R^2) is a numerical formation where indicates, 1 indicates the best, 0 or < 0 indicates worse. If the extent of loss function is high, it means algorithm is presentation a lot of alterations the consequence and desires be amended (Zhang, Cui and Zhu, 2021).

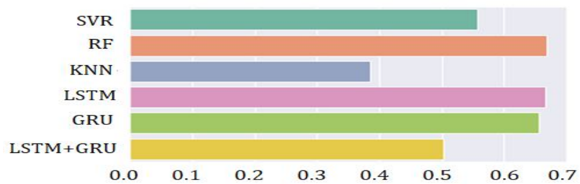


Figure 1: Application of algorithms, loss and accuracy

Observations: RF Algorithm appears the highest Test Scores (Figure:1), that is near about 0.7. The. Another applied algorithms LSTM and GRU reflects as usual and expected outcomes, another side, scores slightly lower than RF. SVR and the LSTM+GRU have similar performance, with scores around 0.5. Another application of KNN algorithms KNN appears comparatively lower scores than others applications.

C. Split data for Training and Testing

The input data is split as training and testing (Figure:2): 65% for Training and 35% for Testing analysis:

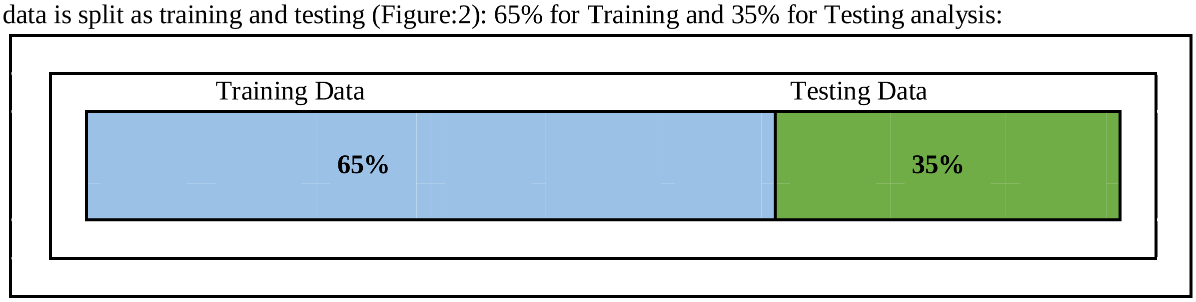


Figure 2: Split data for training and testing

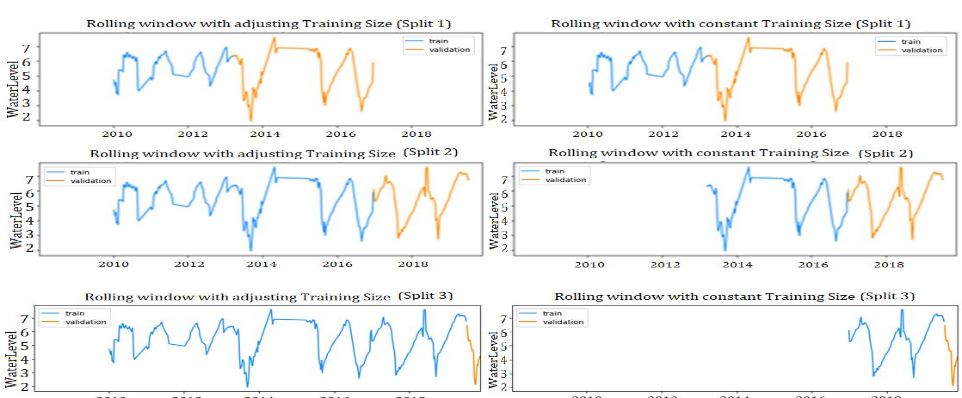
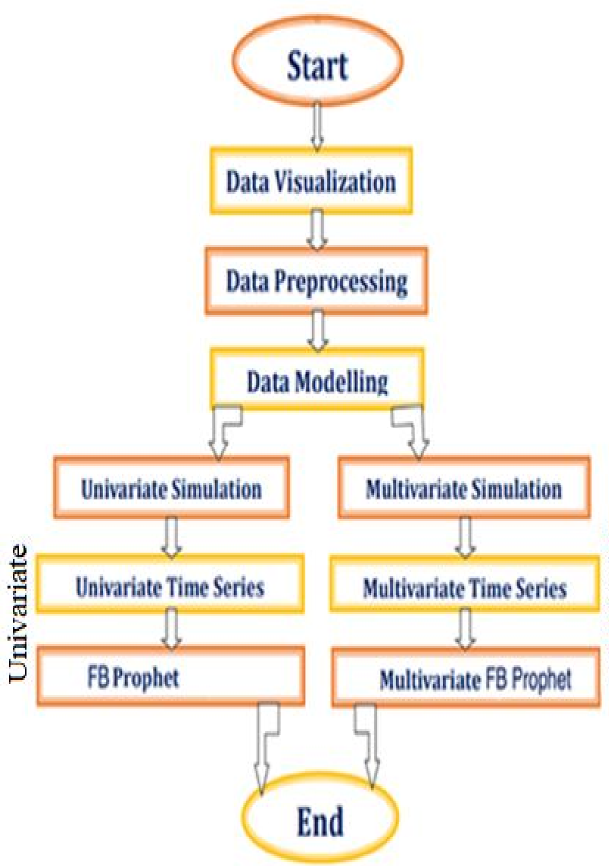


Figure 3: Split data (Water Level): Training and Testing analytics

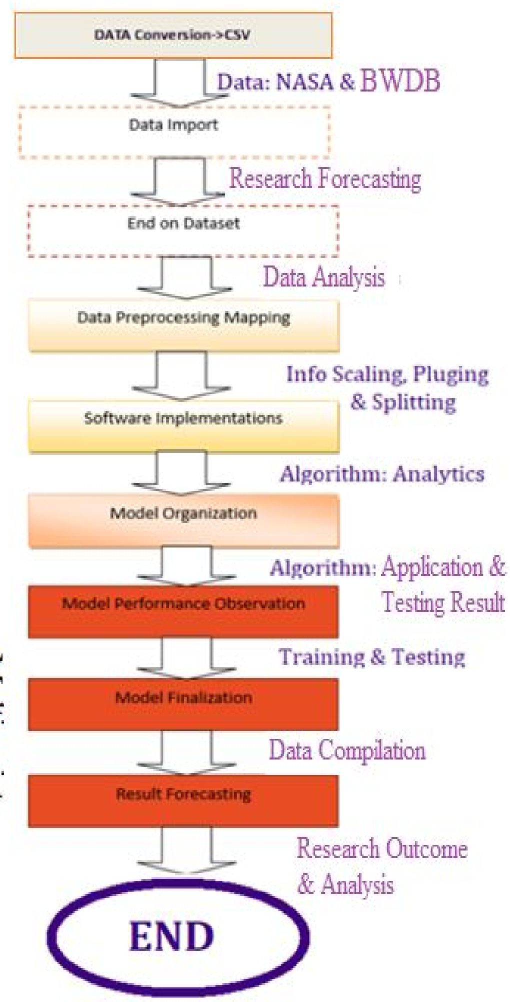
Observations: In (Figure 3) image shows different strategies for validating sliding window time series, comparing approaches that adjust training size using three data splits with tactics that have a constant training size.

- Rolling Window with Adjusting Training Size: In this technique, the training data gets progressively larger with each split, as new data is further to the training set while existing data is reserved for authentication. The training period (blue line) stretches over time, while the authentication period (orange line) leftovers a fixed size until the end of each window. (Wani, M. H. and Kumar, 2021).
- Rolling Window with Constant Training Size: In this method, the training size remnants constant, and old data is "dropped" to maintain the same window size. The training period (blue line) is consistently brought forward, directly followed by the validation period (orange line).
- Split-specific explanations: Across the above three splits, the authentication period for each sliding window approach remains the same. The main transformation is in the performance of the training data. Altering the training size causes past data to accrue. A constant training size preserves a fixed-length window, which is more apposite for steady-state procedures where older data may be less applicable (Zhang and Choi, 2019).
- Data trends: The graph signifies a time series (water levels) with substantial periodic or cyclical dissimilarity. The validation set reliably covers a set of peaks and valleys that are significant for model assessment.

D. Model Setup for data collection and research formation (flowchart:1 and 2)



Flowchart 1: Applicable research forming



Flowchart 2: Research and process flow

E. Research Design and formation of the process flow (flowchart:1 and 2)

Time series prediction to forecast the future groundwater levels, considering factors such as water table depth, parapet height, and geographical directs (Table:1).

SL	DISTRICT	UPAZILA	WELL ID	OLD ID	waterLevel	RL PARAPET (m)	PARAPET HEIGHT (m)	DEPTH (m)	LATITUDE	LONGITUDE
5	Rajshahi	Bagha	GT8110012	RJ116	3.85	14.27	0.35	25.36	24.1851	88.8397
9	Rajshahi	Bagha	GT8110012	RJ116	5.40	14.27	0.35	25.36	24.1851	88.8397
3	Rajshahi	Bagha	GT8110012	RJ116	4.32	14.27	0.35	25.36	24.1851	88.8397
4	Rajshahi	Bagha	GT8110012	RJ116	4.56	14.27	0.35	25.36	24.1851	88.8397
31	Rajshahi	Bagha	GT8110012	RJ116	6.11	14.27	0.35	25.36	24.1851	88.8397

Table 1: water table depth, parapet height, and geographical directs.

```
# 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	Rajshahi	Bagha	GT8110012	RJ116	04-01-2010	4.71	14.27	0.35	25.36	24.1851	88.8397
1	2	Rajshahi	Bagha	GT8110012	RJ116	11-01-2010	4.60	14.27	0.35	25.36	24.1851	88.8397
2	3	Rajshahi	Bagha	GT8110012	RJ116	18-01-2010	4.32	14.27	0.35	25.36	24.1851	88.8397
3	4	Rajshahi	Bagha	GT8110012	RJ116	25-01-2010	4.56	14.27	0.35	25.36	24.1851	88.8397
4	5	Rajshahi	Bagha	GT8110012	RJ116	01-02-2010	3.85	14.27	0.35	25.36	24.1851	88.8397

Table 1a: water table depth, parapet height, and geographical directs (Rename columns).

Here have edited the renamed DATE TIME column with date and WATER TABLE (m) column with GWL.

Application and Summary of SVR, RF, KNN, LSTM, GRU, LSTM+GRU algorithms. This graph provides a visual comparison of the performance of different machine learning algorithms in predicting GWL in Rajshahi (Table:2)

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	0.258153	0.419721	0.066643	0.176166	0.209536	0.314044	0.688519	0.510212	0.687945	0.509543	0.036970	0.109592	0.047702	0.124680
Random Forest	n_estimators=100 ,random_state=1	0.119345	0.420378	0.014243	0.176718	0.088555	0.330257	0.933322	0.508009	0.933306	0.508007	0.009655	0.115933	0.011010	0.130269
K Nearest neigbor	n_neighbors=15,metric=minkowski	0.301204	0.418054	0.090724	0.174769	0.230530	0.316943	0.576449	0.516964	0.575184	0.513432	0.049182	0.109442	0.064608	0.125084
LSTM	loss=mse,optimizer=adam,3 lstm layers with 32 ...	0.330093	0.416833	0.108961	0.173750	0.265163	0.294702	0.510917	0.532596	0.489787	0.516270	0.057897	0.107956	0.076907	0.124033
GRU	loss=mse,optimizer=adam,4 gru layers with 32 n...	0.384603	0.448451	0.147919	0.201109	0.317536	0.318361	0.528435	0.573497	0.307367	0.440101	0.077462	0.125773	0.103827	0.144720
LSTM+GRU	loss=mse,optimizer=adam,2 gru and 2 lstm layer...	0.317535	0.398500	0.100828	0.158802	0.243857	0.295726	0.528354	0.557886	0.527871	0.557885	0.054751	0.102562	0.071945	0.114904

Table 2: visual comparison of the performance of different machine learning algorithms

III. MODELING AND SIMULATION

A. Univariate Time Series Forecasting for Groundwater Level (GWL)

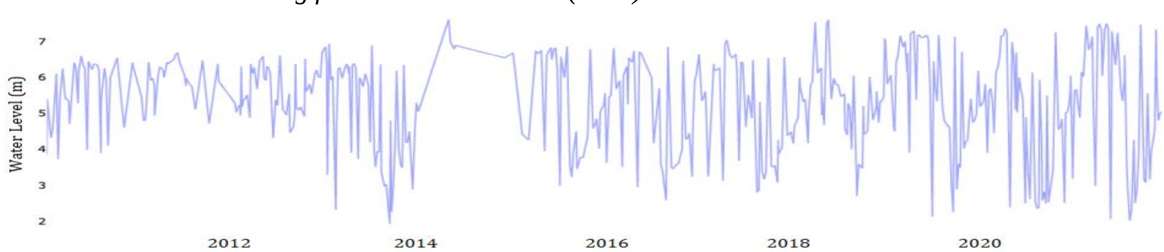


Figure 4: GWL chart, water level for Rajshahi

Observations: The frequency and amplitude of fluctuations appear to be relatively constant over the years (Figure 4). This suggests a stable long-term pattern despite short-term fluctuations. There does not appear to be any clear long-term trend of water levels rising or falling during this period. This figure provides a good visualization of the dynamic nature of groundwater levels in Rajshahi, showing both seasonal patterns and annual fluctuations (Fawaz, Forestier and Weber, 2019).

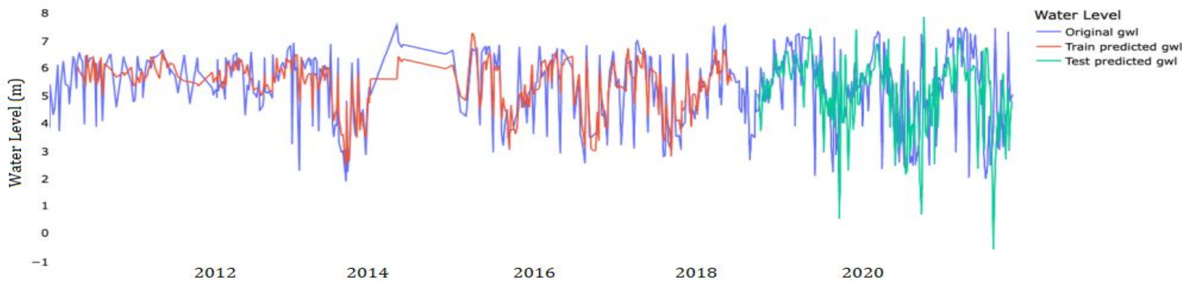


Figure 5a: Original Vs predicted GWL of Rajshahi by SVR

Observations: The usual sample suggests (Figure:5a) seasonal fluctuations in groundwater degrees, with better degrees usually happening at everyday intervals. The version`s predictions appear to seize the overall fashion of the data, however war with a number of the greater intense fluctuations, in particular withinside the check set. The contrast lets in for an assessment of the way properly the SVR version plays in predicting groundwater degrees, each for the education length and the check length.

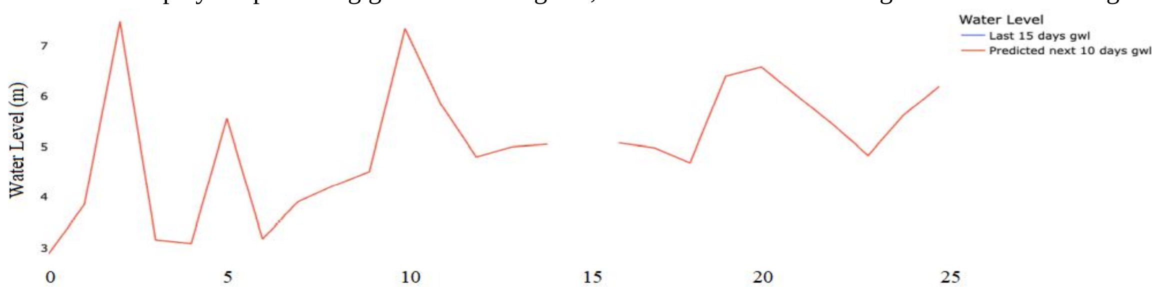


Figure 5b: Plotting last 15 days and next predicted 10 days by SVR

Observations: Iin this area have Plotted the last 15 days and the next forecast 10 days: Here (Figure 5b) compares the last and the next GWL of Rajshahi using the SVR analytics.

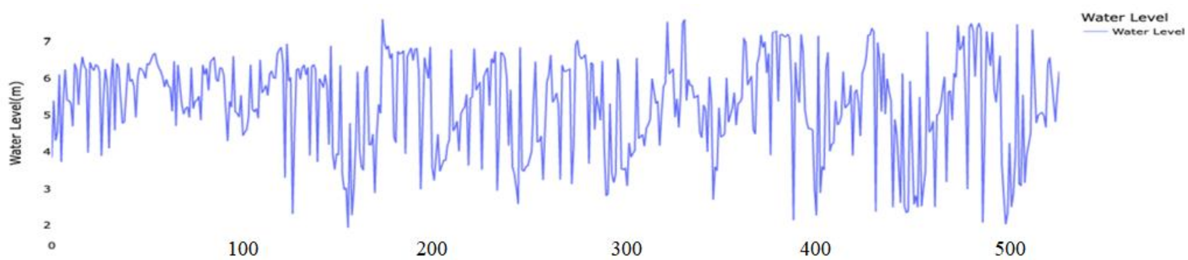


Figure 5c: Plotting GWL with the next 10 days' prediction by SVR

Observations: The provided image appears (Figure 5c) to depict a time-series graph representing water level fluctuations over a given period or series of observations. The graph shows significant variability in water levels, ranging from approximately 2 meters to 7 meters. The fluctuations do not appear to follow an increasing or decreasing trend over time, indicating potentially random or periodic variations.

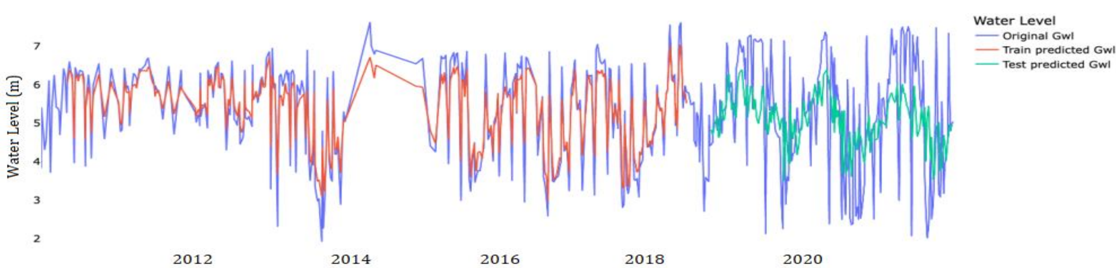


Figure 6a: Comparison between original GWL vs predicted GWL chart of Rajshahi by RF

Observations: Both the training and testing predictions are displayed (Figure 6a) to capture the general trend and seasonality of the original data. There are some discrepancies between the original and predicted values, especially in the extreme high and low values. The water level shows a cyclical pattern, which likely corresponds to seasonal changes. The water level fluctuations over the period appear to be between 2 and 7 meters.

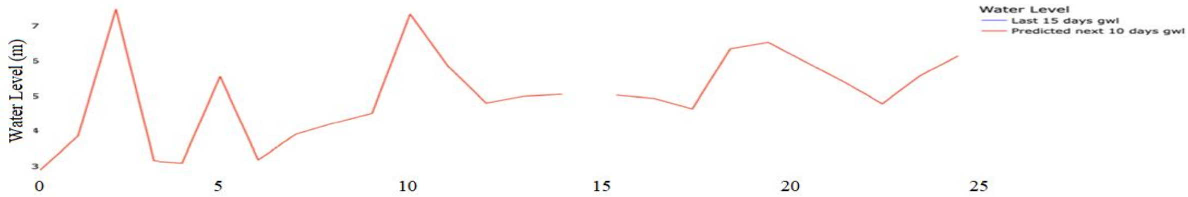


Figure 6b: Plotting last 15 days and next predicted 10 days by RF

Observations: Iin this area have Plotted the last 15 days and the next forecast 10 days: Here (Figure 6b) compares the last and the next GWL of Rajshahi using the RF analytics.

Plotting the last 15 days and the next predicted 10 days the below figure compares with the last and the next predicted GWL of Rajshahi by applying RF analytics.

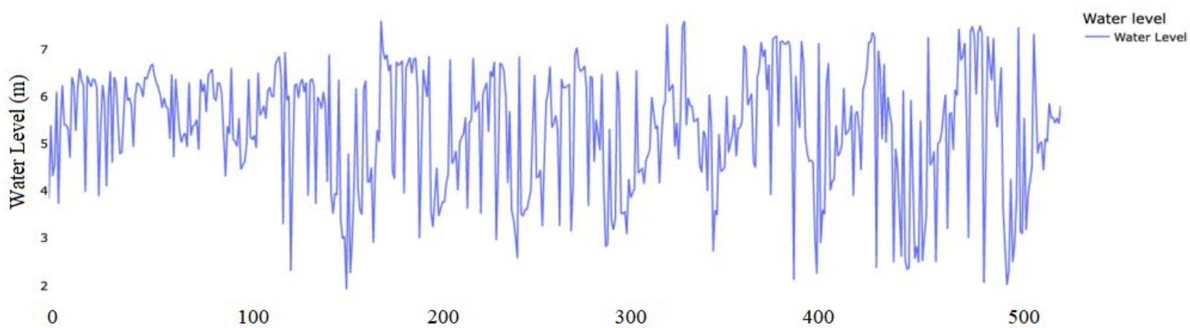


Figure 6c: Plotting whole GWL with next 10 days' prediction of Rajshahi by RF

Observations: The water levels fluctuate between approximately 2 meters and 7 meters, consistent with the earlier image. Here shows (Figure 6c) sharp and frequent changes, suggesting dynamic and possibly volatile conditions. There is no clear increasing or decreasing trend visible over the time series, indicating that the data might represent either natural variability or periodic factors. The x-axis represents observation points or time intervals, reaching above 500 data points.

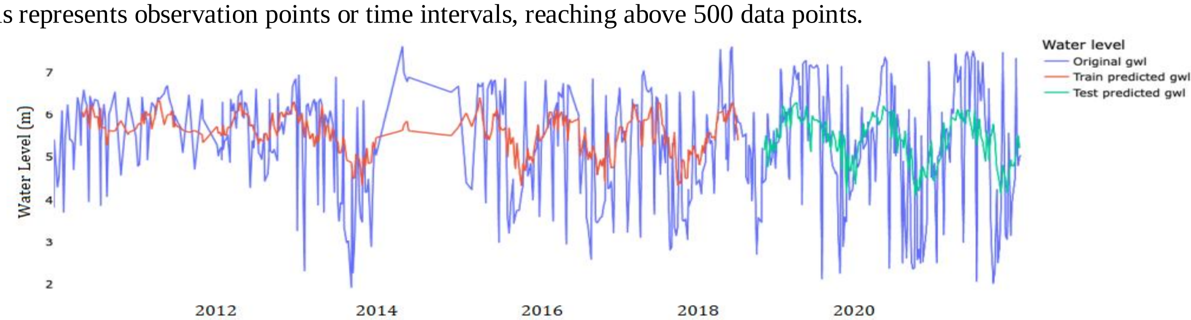


Figure 7a: Comparison between original GWL vs predicted GWL with chart of Rajshahi by KNN

Observations: The test predicted GWL (green line) emerges from around 2018 (Figure 7a) and follows the general pattern of the original GWL, but with lower accuracy compared to the training period. Both the training and test predictions seem to capture the general trend, but miss some of the sharp peaks and valleys present in the original data. The water level shows a cyclical pattern, which likely corresponds to seasonal changes. Water level fluctuations throughout the entire period are seen to be between 2 and 7.5 meters.

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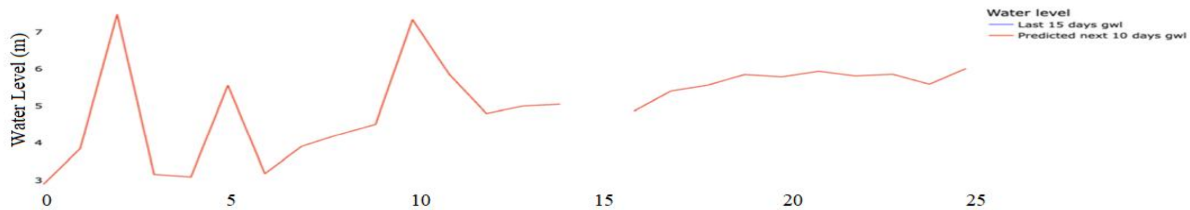

Figure 7b: Plotting last 15 days and next predicted 10 days of Rajshahi by KNN

Observations: Iin this area have Plotted the last 15 days and the next forecast 10 days: Here (Figure 7b) compares the last and the next GWL of Rajshahi using the KNN analytics.

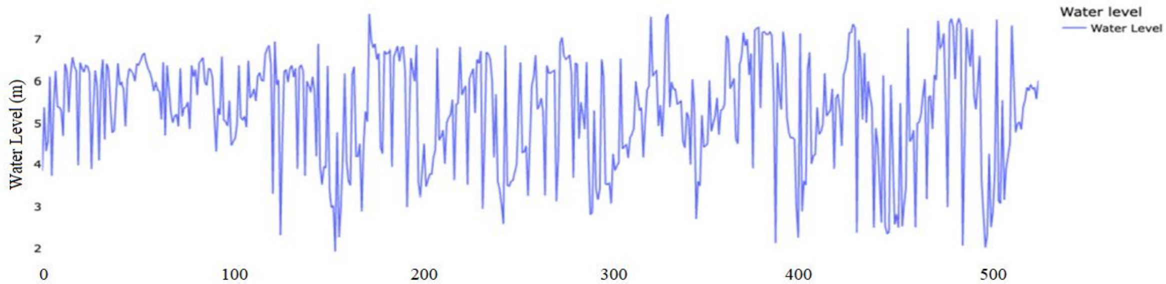

Figure 7c: Plotting whole GWL with next 10 days' prediction of Rajshahi by KNN

Observations: The water levels fluctuate (Figure 7c) between approximately 2 meters and 7 meters, consistent with the earlier image. Here shows sharp and frequent changes, suggesting dynamic and possibly volatile conditions. The x-axis represents observation points or time intervals, reaching above 500 data points.

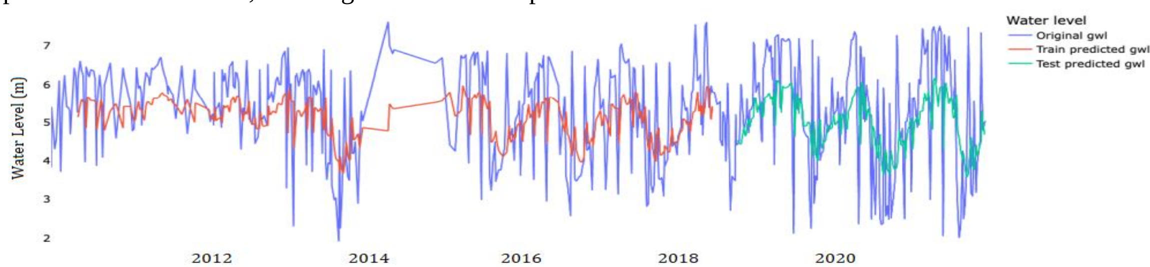

Figure 8a: Comparison of original GWL price vs predicted GWL chart of Rajshahi by GRU

Observations: The GRU model (Figure 8a) seems to capture the general trend and seasonality of groundwater levels quite well, but it tends to underestimate extreme values, and there are periods when the predictions deviate significantly from the original data, especially during rapid fluctuations.

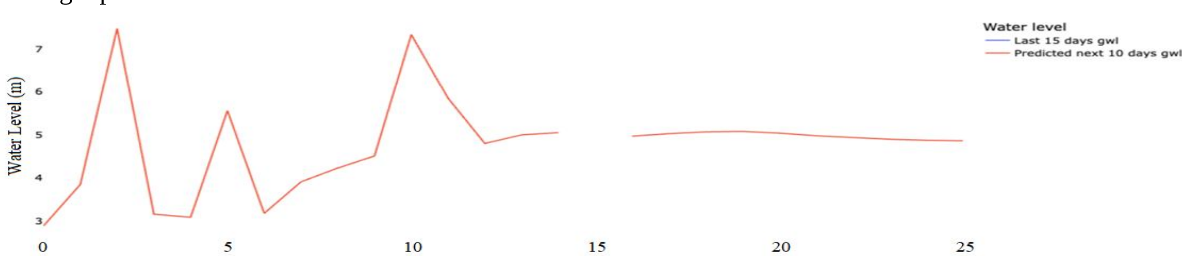

Figure 8b: Plotting last 15 days and next predicted 10 days of Rajshahi by GRU

Observations: Iin this area have Plotted the last 15 days and the next forecast 10 days: Here (Figure 8b) compares the last and the next GWL of Rajshahi using the GRU analytics. The prediction (red line) suggests that the water level will stabilize around 5 meters for the next 10 days, with only minor fluctuations. The transition from historical data to prediction appears smooth, indicating that the GRU model has captured the recent trend in water levels.

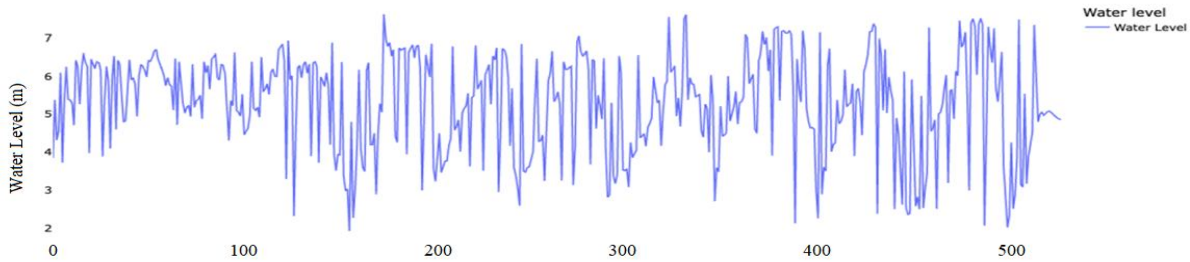

Figure 8c: Plotting whole GWL with next 10 days prediction of Rajshahi by GRU

Observations: The most recent part of the graph towards the right seems to show predicted values for the next 10 days, though it's not clearly distinguished from the historical data. The overall pattern suggests a cyclical nature to the water levels, with periods of higher and lower levels repeating over time.

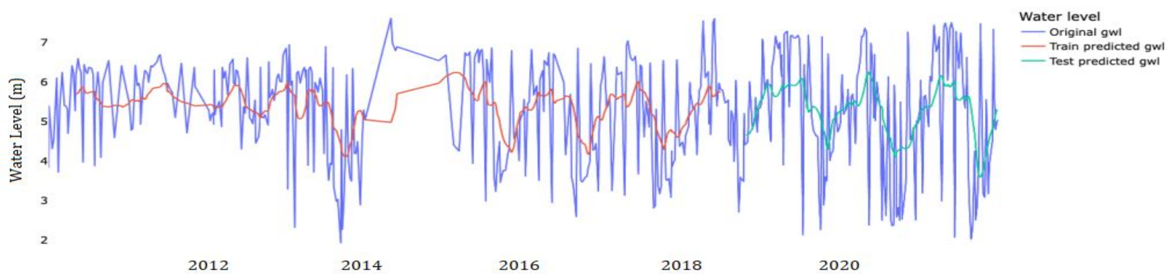

Figure 9a: Comparison between original GWL vs predicted GWL chart of Rajshahi by LSTM

Observations: The LSTM model (Figure 9a) seems to capture the general seasonal patterns and trends in groundwater levels. During some periods, the predictions (both training and testing predictions) deviate significantly from the original data, especially in the case of sudden fluctuations or extreme values. This graph suggests that the LSTM model is performing quite well in predicting groundwater levels in Rajshahi, but it may have difficulty capturing some of the extreme fluctuations in the data.

Figure 9b: Plotting last 15 days and next predicted 10 days of Rajshahi by LSTM

Observations: The LSTM algorithm seems (Figure 9b) to predict a stabilization of water levels in the near future, despite the recent fluctuations. The prediction doesn't show any significant peaks or troughs, suggesting an expected period of relative stability in ground water levels.

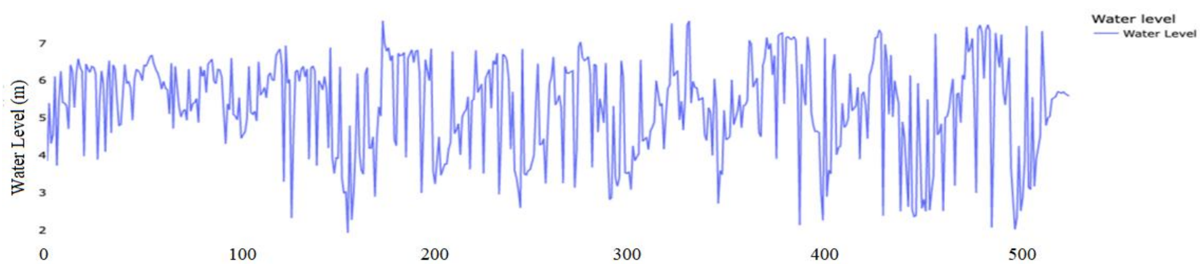

Figure 9c: Plotting whole GWL with next 10 days' prediction of Rajshahi by LSTM

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Observations: The overall pattern seems *(Figure 9c)* to repeat, but with some variations in the exact heights of peaks and depths of troughs. There's no clear long-term trend visible; the water levels appear to oscillate around a relatively stable mean over the entire period. The frequency of the oscillations appears to be fairly consistent throughout the time series, with multiple cycles visible within each 100-timestamp interval.

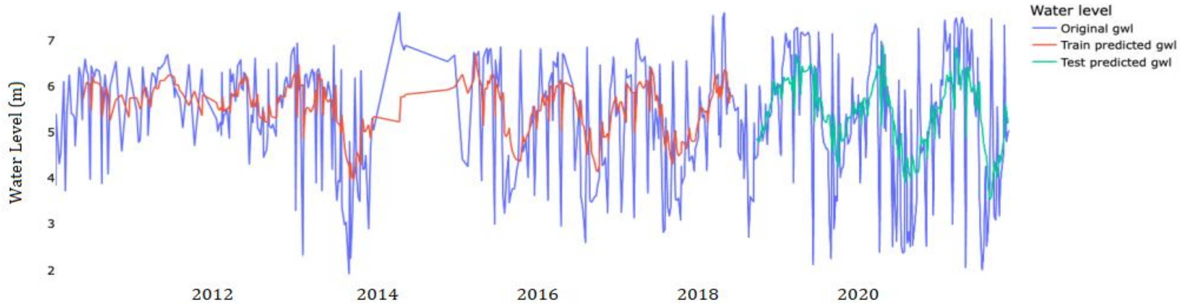

Figure 10a: Comparison between original GWL vs predicted GWL chart of Rajshahi by LSTM+GRU

Observations: The LSTM+GRU model (Figure 10a) appears to capture the general trends and seasonality of groundwater levels quite well, but tends to underestimate extreme values.

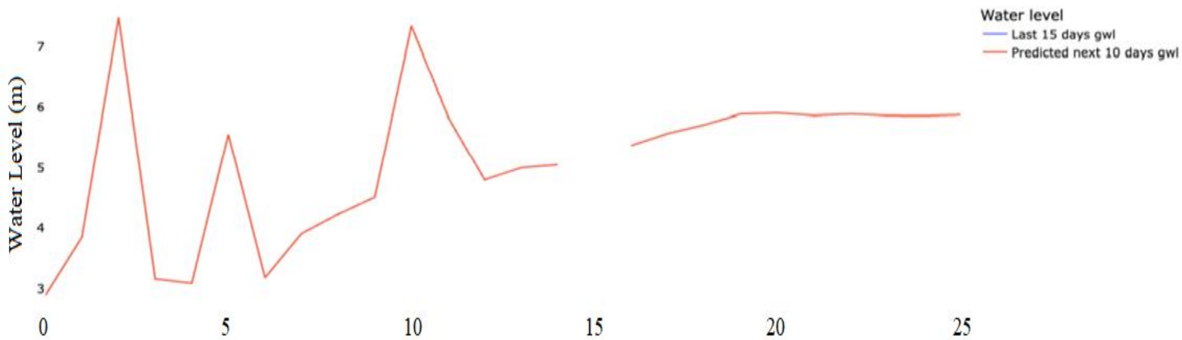

Figure 10b: Plotting last 15 days and next predicted 10 days of Rajshahi by LSTM+GRU

Observations: The transition from historical data to prediction appears (Figure10b) smooth, indicating that the LSTM+GRU model has captured the recent trend in water levels. The prediction suggests a more stable water level in the coming days, with a slight upward trend, compared to the volatility seen in the past 15 days.

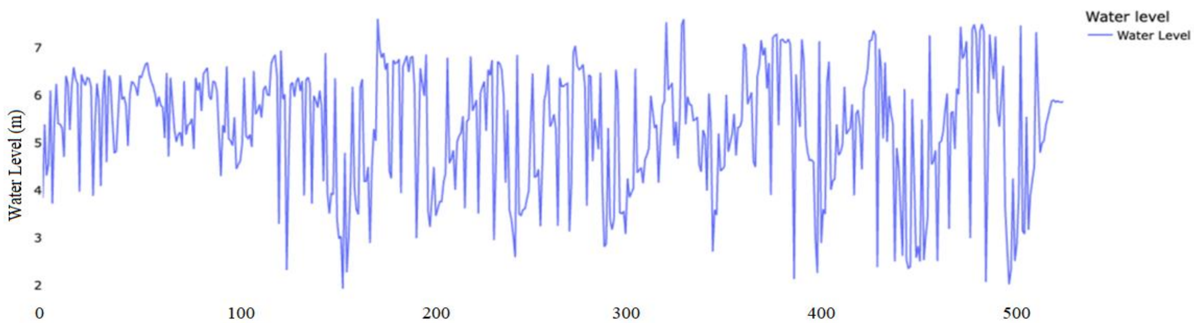

Figure 10c: Plotting whole GWL with next 10 days' prediction of Rajshahi by LSTM+GRU

Observations: The fluctuations seem to become more pronounced and frequent towards (Figure 10c) the end of the timeline. The graph shows both historical data and predictions, as indicated by the title mentioning "prediction". This visualization provides a comprehensive view of groundwater level changes in Rajshahi over time, which could be useful for water resource management, environmental monitoring, and planning purposes.

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B. Multivariate Time Series Forecasting: Modelling and Simulation

The application of the Groundwater Level (GWL), Rainfall, Temperature, Root and Surface Soil Witness, Depth to Groundwater level at the Rajshahi Zone of Bangladesh.

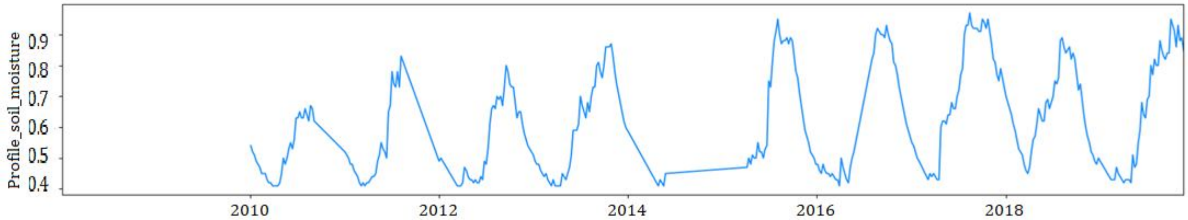

Figure 11: Multivariate Time Series analytics for Soil Moisture, Rajshahi area

Observations: The low points are typically around 0.4 to 0.5 (Figure 11). Overall, the peaks increase over time, with the highest peaks occurring in the later years on the graph. The cyclical pattern appears to be fairly consistent over the years, although there is some variability in the exact timing and height of the peaks and troughs.

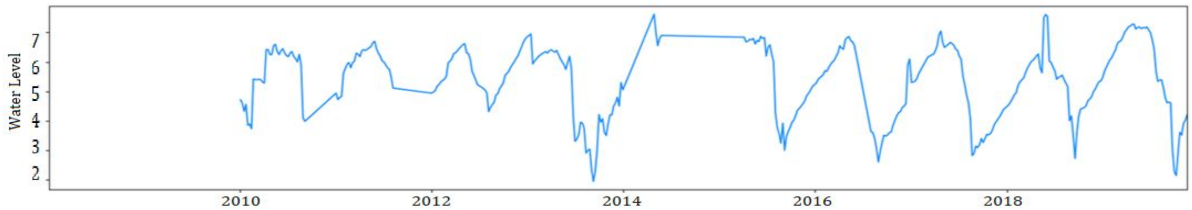

Figure12: Multivariate analysis, water level, Rajshahi zone

Observations: It shows a cyclical pattern (Figure: 12) with regular peaks and valleys. The highest peak reaches about 7 units, while the lowest point drops to about 2-3 units. The pattern varies greatly from year to year.

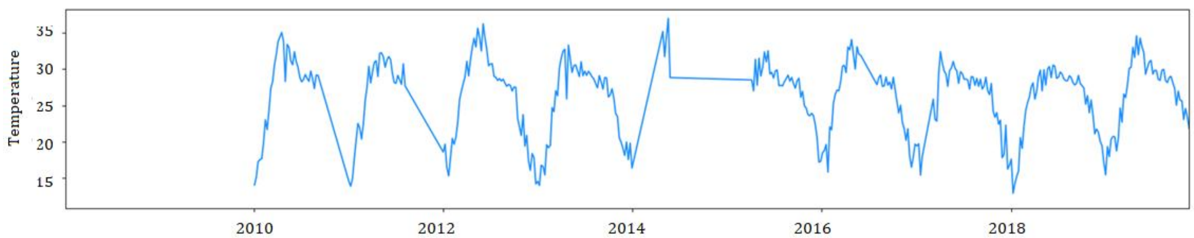

Figure 13: Multivariate analysis, temperature, Rajshahi zone

Observations: It shows a cyclical pattern (Figure: 13), but fluctuates more frequently. Maximum temperatures reach about 35°C and minimum temperatures reach about 15°C. Temperature patterns are more consistent from year to year than water levels.

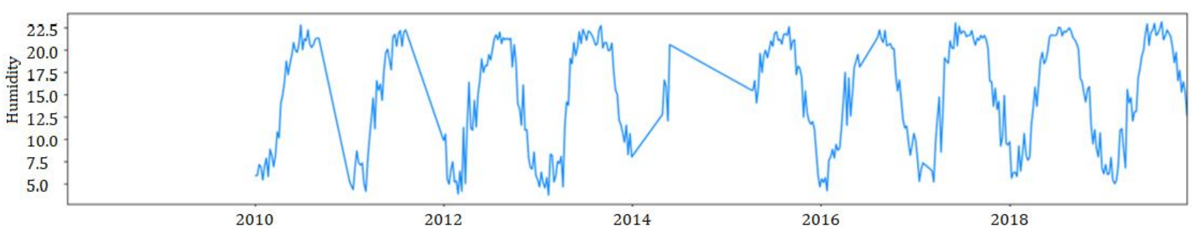

Figure 14: Multivariate analysis, humidity, Rajshahi zone

Observations: The highest peak reaches about 20-22 units (Figure 14), and the lowest point decreases to about 5-7 units. Pattern varies somewhat from year to year, but overall periodicity remains constant.

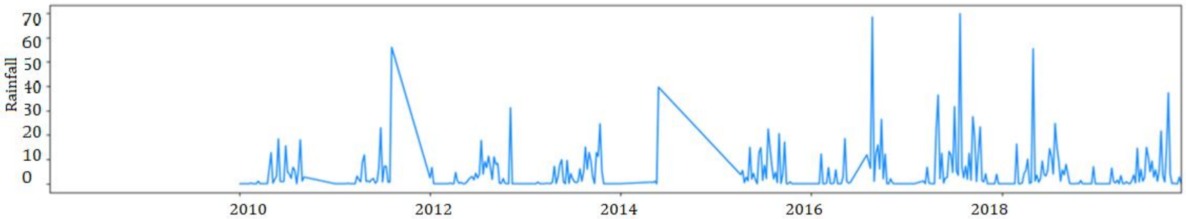

Figure 15: Multivariate analysis, humidity, Rajshahi zone

Observations: It shows a more irregular pattern (Figure: 15) with sharp irregular peaks. Most of the time, the amount of precipitation is close to zero, but there are occasional sudden increases in precipitation. The highest peaks reach a maximum of about 70 units, but many periods have no precipitation.

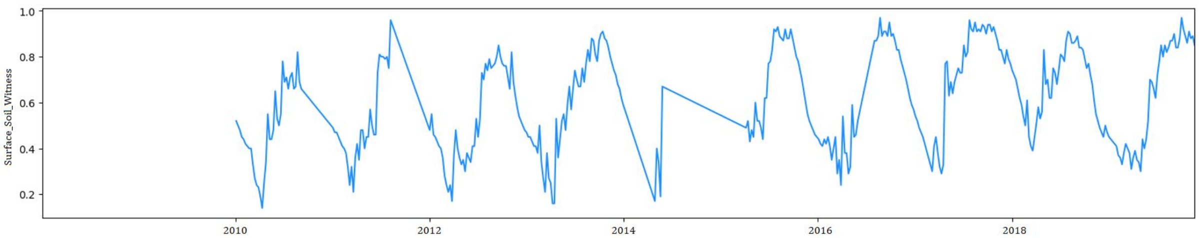

Figure 16: Multivariate Analysis (surface soil witness), Rajshahi

Observations: There are slight changes in the pattern (figure 16), especially in the timing and height of some of the peaks and valleys. The cyclical nature of the data means that there is a strong seasonal effect on what is being measured.

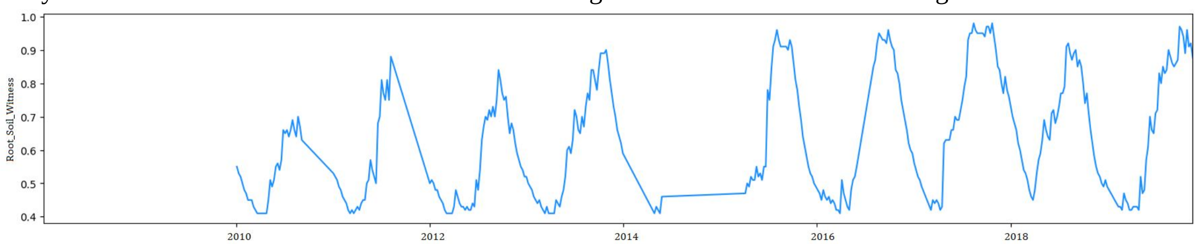

Figure 17: Multivariate Analysis (root soil), Rajshahi

Observations: Here shows a clear periodic pattern with roughly equal regular peaks and valleys (figure: 17). These figures show that there is year-to-year variation in the shape and amplitude of the cycles. The graphs can represent the same kind of data at two different locations or under slightly different conditions. The periodic nature of the data means that there is a strong seasonal effect on what is being measured.

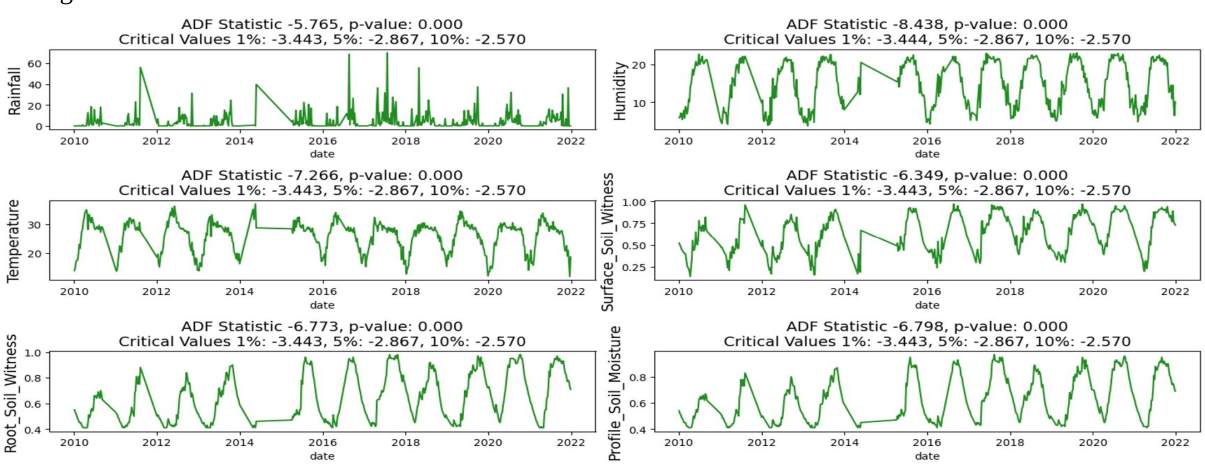

Figure 18: Multivariate Series (Soil, Temperature, Humidity, Rainfall, Surface Soil witness)

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Observations: This image shows six-time series graphs (Fig: 18) of different environmental variables from 2010 to 2022. Each graph contains the Augmented Dickey-Fuller (ADF) test statistic and critical values used to determine if the time series is stationary or not.

- Rainfall: Shows sporadic peaks indicating periodic heavy rain events. The pattern seems to be seasonal with higher peaks in certain months.
- Humidity: Shows a clear cyclical pattern with regular fluctuations, possibly representing seasonal changes in humidity.
- Temperature: Exhibits a seasonal pattern with higher temperatures during the summer and lower temperatures during the winter.
- Surface soil moisture: Exhibits cyclical fluctuations and may be related to seasonal precipitation and temperature patterns.
- Root-Zone Soil Wetness: Exhibits a similar cyclical pattern as surface soil moisture, but with slightly different amplitudes.
- Profile Soil Moisture: displays cyclical patterns that may be related to other soil moisture measurements.

All graphs have negative ADF test statistics with p-values of 0.000, indicating that these time series are stationary. The critical values of the ADF test are the same for all charts: -3.443 (1%), -2.867 (5%), and -2.570 (10%). These graphs provide a comprehensive overview of different environmental factors over time and can be useful in climate research, agricultural planning, and water resources management.

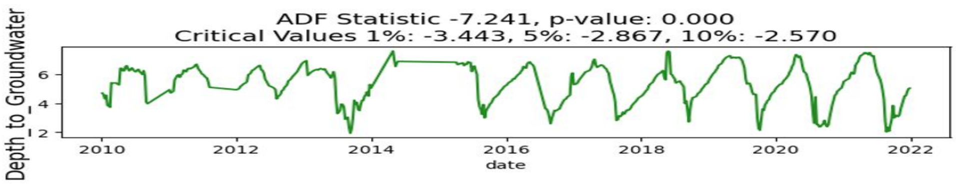

Figure 19: Time Series Analysis (periodical status)

Observations: This pattern appears to repeat (Figure 19), with some years showing more extreme fluctuations. The graph title includes the statistics: ADF statistic: -7.241, p-value: 0.000, critical values: 1%: -3.443, 5%: -2.867, 10%: -2.570. The ADF (Augmented Dickey-Fuller) test results suggest that this time series is stationary, as the test statistic (-7.241) is more negative than the critical value and the p-value is very low (0.000). There appears to be some variability in the amplitude of the cycles from year to year, which may indicate that environmental conditions or water use patterns are changing over time.

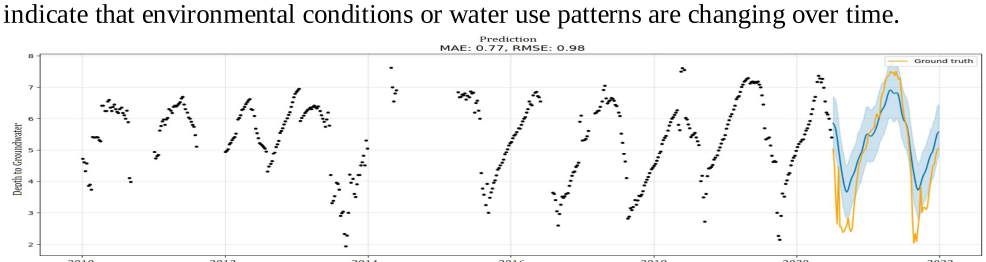

Figure 20: Prediction – MAE & RMSE, Depth to GWL analysis, Multivariate – Rajshahi

Observations: These values suggest that the model predictions are fairly accurate, with an average error of less than 1 meter (Figure 20). The predictions appear to capture the general trends and seasonality of groundwater depth, but there are a few points where they overestimate or underestimate the actual values.

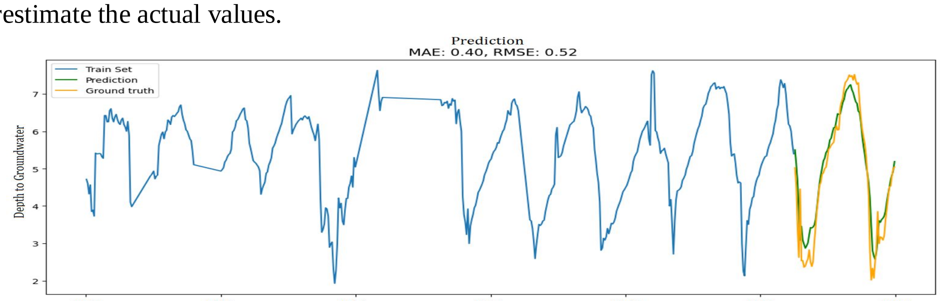

Figure 21: Time Series: FB Prophet Model Output, MAE, RMSE – Multivariate, Rajshahi

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Observations: The green prediction line closely follows the orange ground truth line (Figure 21), indicating that the model is performing well. These values suggest that the model's predictions are fairly accurate, with an average error of less than 0.5 meters.

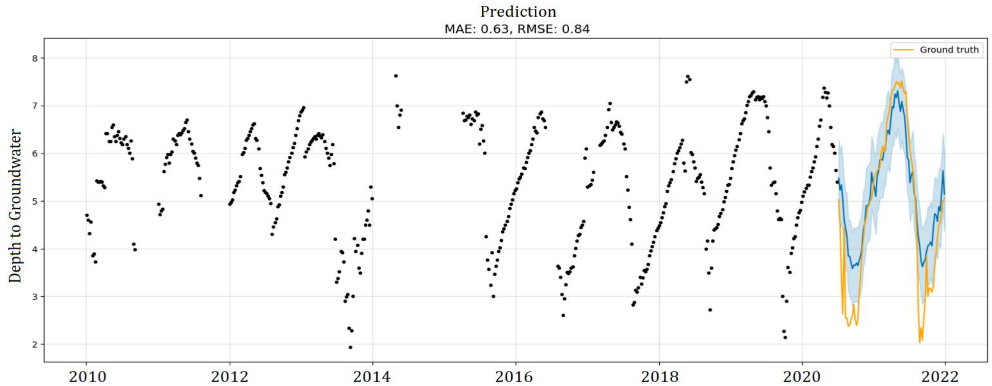

Figure 22 Multivariate Time Series Analysis: FB Prophet Model Output, Rajshahi

Observations: This image shows a time series plot of groundwater depth predictions from 2010 to 2022 (Figure 22). These values suggest that the model predictions are fairly accurate, with an average error of less than 1 meter. The predictions appear to capture the general trends and seasonality of groundwater depth, but there are a few points where they overestimate or underestimate the actual values.

IV. FINDINGS & RECOMMENDATIONS

A. Major Findings

1) Temporal Dependencies: DL and ML models can classify lagged relations and cyclical patterns that should distress the behavior of variables over time.
2) Nonlinear Relationships: This research may reveal nonlinear relationships and interactions between ecological variables, such as Neural Networks. These are well suited to capture the complex and nonlinear aspects of changes in multivariate time series data.
3) Variable Importance: By examining the associations of predictive model features, the most important influences leading to changes in groundwater levels and soil moisture content are identified, which may aid in prioritizing management actions and activities aimed at protecting water resources and improving ecosystem resilience.
4) Prediction Accuracy: In this research field, we have observed superior computational accuracy of DL and ML models in relation to traditional statistical approaches to time series forecasting (Karthikeyan, Khosa, and Singh, 2020).
5) Long-Term Trends: By examining historical data and projecting future conditions, the study could classify long-term trends and variations in groundwater availability, precipitation regimes, and soil moisture dynamics associated with climate change and anthropogenic impacts. This information could update adaptation approaches and ingenuity in water resource forecasting.
6) Uncertainty Analysis: The observation could calculate the uncertainty associated with the version forecasts and investigate the sensitivity of effects to the variations in enter parameters, version structures, and figures sources. Uncertainty breakdown may want to find the money for to the decision-makers with an extra nuanced thought of the reliability and regulations of predicting consequences.
7) Management Strategies: Based on the study findings, adaptive management approaches and policy references for sustainable water resource management and ecosystem protection can be recommended. This may include improved irrigation planning, application of water-saving technologies, establishment of groundwater recharge protection areas, etc.
8) Interdisciplinary Insights: The interdisciplinary nature of this study may encourage relationships between hydrologists, climatologists, agronomists, and data scientists to address complex water-related challenges from multiple perspectives (Mojid, Parvez, Moinuddin, Hodgson, 2019).
9) Performance of the applied Algorithms: The use of different forecasting models such as SVR, RF, KNN, LSTM, GRU, and LSTM+GRU were effectively evaluated to provide predictable results. The models showed varying accuracy in predicting groundwater levels, with some models performing better than others under certain circumstances.

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B. Major Recommendations

1) Data Quality and Availability: Ensure high quality and consistency of data for all variables of awareness including groundwater levels, precipitation, temperature, and soil moisture. Use multiple data sources such as weather stations, surface sensors, and groundwater monitoring sites to capture spatial and temporal variation.
2) Feature Engineering: Perform systematic feature engineering on abstract and expressive predictors from raw data. Consider integrating lagged variable sets, seasonal indicators, and meteorological indicators to capture temporal shape and dependencies.
3) Multivariate Modeling: Implement multivariate time series estimation models to simultaneously forecast multiple variables of interest. This makes it possible to capture complex interactions and response loops among a set of ecological variables (Abdollahi, Bazrafshan, Razmjooy, 2020).
4) Data Preprocessing: Process and back up the data wisely, handle missing principles, outliers, and seasonality. Normalize the input variables so that they are on a similar scale and promote convergence during training (Lundberg and Lee, 2017).
5) Model Training and Validation: Split the dataset into training, validation, and test sets to evaluate the performance of the model. Use the training data to train the model and the validation set to certify the model (Cheng and Castelletti, 2020).
6) Joint Approaches: Consider using a common approach to combine estimates from multiple models or model alternatives. Ensemble techniques such as bagging, boosting, and stacking can improve prediction accuracy and robustness by leveraging the strengths of different algorithms.
7) Interpretability and Explainability: Develop interpretability of predictive models by investigating feature importance, variable contributions, and model predictions.
8) Model Evaluation Metrics: Choose the right evaluation metrics to assess the accuracy and reliability of predictive models. Common metrics are MAE, MSE, RMSE, and R2.
9) Uncertainty Quantification: Measure the uncertainty associated with model predictions and assess the sensitivity of results to differences in input parameters and model assumptions (Aishwarya and Vasudevan, 2023).
10) Validation and Application: Validate predictive models using independent datasets and real-world observations to determine their generalizability and applicability in valid contexts.

V. RESULTS

A. Loss Score

Losses arise from three loss functions for six defined algorithms for Rajshahi city (Figure: 23). MAE causes the most loss among the six algorithms. The value varied between 0.22 and 0.45. Due to divergence, the losses of MSE and RMSE became correspondingly smaller. The amount of loss caused by MSE varied between 0.21 and 0.13 for SVR and LSTM+GRU. So the trend for MSE was similar: the loss decreased from RF to LSTM. The loss increased to 0.16 for GRU, then decreased to 0.13 for LSTM+GRU.

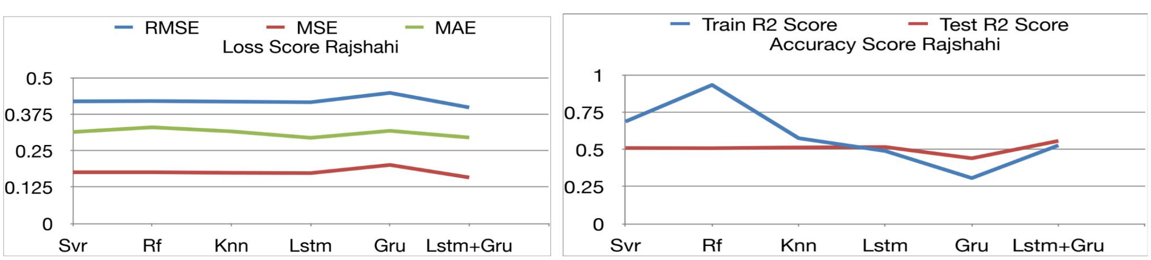

Figure 23: Accuracy Score Rajshahi

B. Accuracy Score

Test R2 Score is the actual accuracy evaluation of the algorithm (Figure: 23). As can be seen from the graph, Train R2 Score and Test R2 Score had different trends. The Train R2 Score value increased by 0.68 to 0.98 for SVR and RF. Then, the Train R2 Score of GRU algorithm dramatically worsened to 0.26. This is the lowest training truth across the six algorithms. Meanwhile, the test R2 scores for SVR and LSTM varied between 0.50 and 0.27. The best accuracy comes from the LSTM and LSTM+GRU algorithms, with 0.50 and 0.51, respectively.

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C. Heatmap of accuracy scores

Correlation of the SVR, RF, KNN, LSTM, GRU, and LSTM+GRU algorithms. Most cells in the heatmap show very high correlation values (close to 1) (Figure 24), as indicated by the bright colors. As expected, each algorithm is perfectly correlated with itself, so the diagonal line of the heatmap shows perfect correlation (1.0) (Fawaz and Weber, 2019).

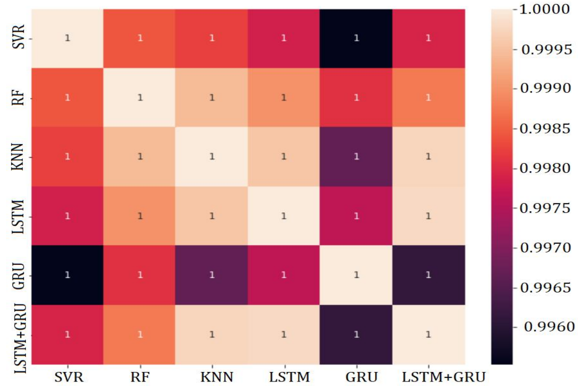

Figure 24: Accuracy Heatmap of Rajshahi

Observations: This heatmap (Figure 24) shows that the algorithms perform similarly in terms of groundwater level prediction accuracy, with only minor differences in the results. A high correlation indicates that the predictions of the different algorithms are consistent. There are some differences in the correlations between different pairs of algorithms, but overall, the correlations are very high overall (Lim and Zohren, 2021).

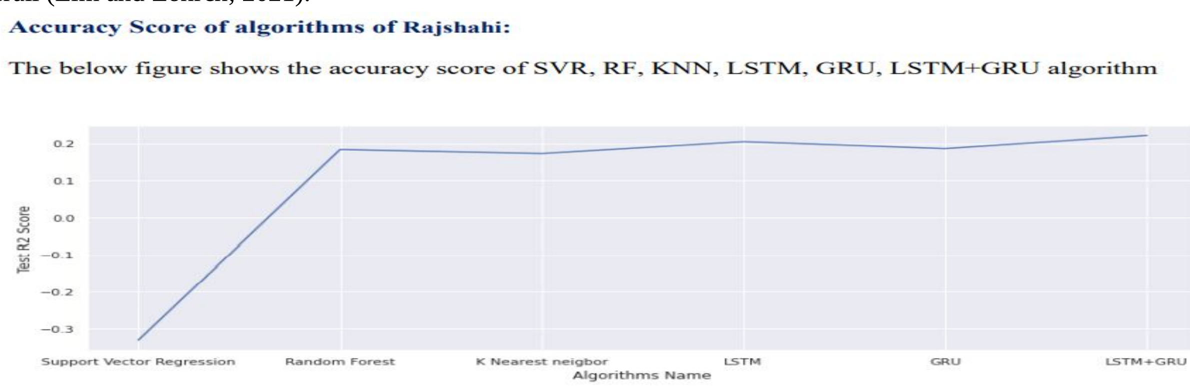

Figure 25: Accuracy Score of algorithms for Rajshahi

Observations: There's a significant improvement (Figure 25) in accuracy from SVR to Random Forest. The accuracy scores for Random Forest, KNN, LSTM, GRU, and LSTM+GRU are all relatively close to each other and positive. SVR has the lowest accuracy score, being the only negative value on the graph. The LSTM+GRU combination appears to have the highest accuracy score, though the difference from the other neural network models (LSTM and GRU) is small (Acharyya, 2017). This graph suggests that for this particular task, the more advanced machine learning algorithms perform better than simpler models like SVR. The combined LSTM+GRU model seems to offer a slight edge in accuracy over the individual models.

VI. CONCLUSION

Predicting the future of artificial intelligence (AI) and neural networks (NN) involves studying current trends, technological developments, and possible applications to make informed predictions about future developments. Computer models of NNs are useful for testing evolving models of thought, such as deliberation, intelligence, and decision-making. Predicting accurate outcomes can be challenging. Understanding current trends and evolving technologies can provide valuable insights into potential directions for AI development. In this study, we combined the power of myriad machine learning algorithms and SVR, RF, KNN, LSTM, GRU, and LSTM+GRU for modeling and simulation by performing deep learning univariate and multivariate time series forecasting with neural network models.

Major division areas of Rajshahi were applied. Considering the underlying mechanisms and values that govern the behavior of these models can be challenging, especially for deep learning architectures with millions of constraints. Train each model using the training data and tune the hyper-constraints using the validation set. Improve model performance using methods such as cross-validation and grid search. Abstract appropriate structures from the raw data that can capture the changing aspects and interactions between variables. These may include lag variables, cyclical indicators, and weather indices. I believe this article is an insightful and comprehensive resource for researchers and experts in the field.

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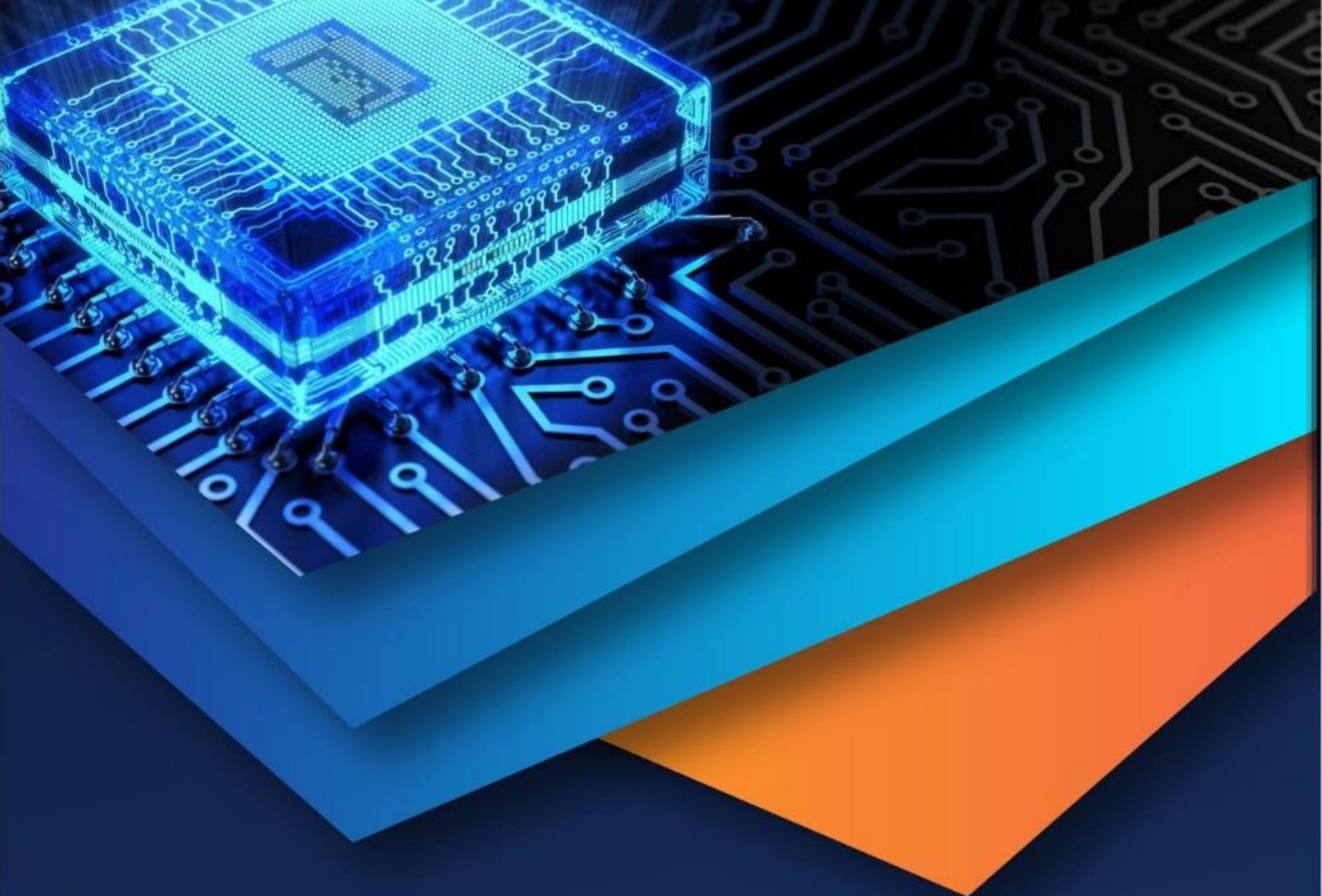

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