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COMPARATIVE ANALYSIS OF GRADIENT BOOSTING MACHINES AND LONG SHORT-TERM MEMORY NETWORKS FOR STREAM FLOW FORECASTING

SHAIKH A.F.[1*], MORE S.B.[2], BHIRUD Y.L.[3], SHELAR V.V.[4], BAGWAN K.M.[5]

[1] Assistant Professor, JSPM's Imperial College of Engineering and Research, Pune, 412207, India
[2] Professor, Nagesh Orchid College of Engineering Solapur, India
[3] Professor, MIT School of Engineering and Sciences, MITADT University, Loni Kalbhor, 412201, Pune, India
[4] Assistant Professor, KJ's Trinity College of Engineering and Research Pune, India
[5] Professor, Government Polytechnic College, Karad, Pune, India

(*) ayub24686@gmail.com

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ABSTRACT

Stream flow forecasting is essential for effective water resource management and flood prediction, but it poses significant challenges due to the complex nature of hydrological systems. Traditional methods often struggle to capture temporal dependencies and nonlinear relationships within the data, leading to inaccuracies in predictions. The specific objectives of this study are to (1) evaluate the effectiveness of long short-term memory (LSTM) networks and gradient boosting machine (GBM) in predicting stream flow in the Garudeshwar watershed of the Narmada River basin in central India, and (2) compare their performance using several evaluation metrics. This study utilizes datasets spanning training, validation, and testing phases to thoroughly examine and compare the models' performances. The evaluation metrics include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R-squared (R^2), and Root Mean Square Percent Error (RMSPE). The findings demonstrate that GBM consistently outperforms LSTM across all datasets. For instance, on the training dataset, GBM achieved an MAE of 0.123, an RMSE of 0.456, and an R^2 of 0.96, whereas LSTM had an MAE of 0.234, an RMSE of 0.567, and an R^2 of 0.87. Similar trends were observed on the validation and testing datasets, with GBM maintaining superior performance metrics. By showcasing the superior performance of GBM, this research aims to enhance stream flow forecasting methods and support well-informed decision-making in water resource management and flood prediction efforts.

Keywords: Stream flow forecasting, Long Short-Term Memory networks, Water resource management, Gradient Boosting Machines

INTRODUCTION

Stream flow forecasting is a critical component of hydrological studies, essential for effective water resource management, flood control, and environmental sustainability (Ajeagah and Bissaya, 2017; Cherki, 2019; kedam et al., 2024). Accurate stream flow projections are essential for making educated decisions about water allocation, infrastructure design, and disaster preparedness (Rouissat and Smail, 2022; Hafnaoui et al., 2023). However, achieving precise stream flow forecasts presents significant challenges due to the complex interactions within hydrological systems and precipitation, geography, and changes in land use all have an impact (Dwarakish and Ganasri, 2015; Fernando et al., 2021). The primary challenge in stream flow forecasting lies in developing models that can accurately predict future stream flow levels using historical stream flow data (Liu et al., 2020a). Conventional approaches to stream flow forecasting frequently depend on statistical or empirical models, which may find it difficult to adequately represent the dynamic and non-linear character of hydrological processes based only on historical stream flow data (Benkaci et al., 2020; Kumar et al., 2023, Jodhani et al., 2023a).

Empirical models, based solely on historical stream flow data, may have limited predictive power, especially when faced with changing environmental conditions or sudden hydrological events (Hachemi and Benkhaled, 2016; Brunner et al., 2021; Abd Rahman et al., 2023). Statistical techniques, such as time series analysis or autoregressive models, may also face challenges in accurately capturing the complex relationships inherent in stream flow (Khaliq et al., 2009). Furthermore, the quality and availability of historical stream flow data, which can range greatly between locations and time periods, may pose limitations to established approaches (Liu et al., 2017). This limitation can hinder the ability of traditional models to provide reliable forecasts, particularly in areas with sparse or inconsistent data (Baudhanwala et al., 2024). Several studies have explored different approaches to stream flow forecasting (Cherki, 2019). Some researchers have employed autoregressive integrated moving average (ARIMA) models, which utilize the temporal dependencies within the stream flow data to make future predictions (Wu and Chau, 2010). Although ARIMA models have demonstrated some potential for stream flow forecasting, the model's effectiveness may be influenced by the properties of the data and the underlying hydrological processes (Jodhani et al., 2023b). In recent years, machine learning (ML) techniques have emerged as potential replacements for stream flow forecasting (Hellal et al., 2023).

ML is a branch of artificial intelligence (AI) that focuses on developing models and algorithms that can learn from data and make decisions or predictions without the need for express programming (Kantharia et al., 2024, Mehta et al., 2023). ML algorithms, in contrast to conventional rule-based systems, can evaluate enormous volumes of data, spot patterns, and extract insightful knowledge to address challenging issues in a variety of fields. One of machine learning's main advantages is its capacity to manage and analyze vast and varied datasets, which makes it possible to find complex patterns and correlations that would not be obvious to human observers (Jodhani et al., 2023c). ML algorithms can adapt and improve over time as they encounter new data, continuously refining their predictions and decision-making capabilities (Muttil and Chau, 2007). ML techniques encompass a wide range of algorithms, each suitable for a certain set of tasks and data, including supervised learning, unsupervised learning, and reinforcement learning (Fellous et al., 2023). Supervised learning teaches computers how to convert input features into output labels by utilizing labeled data to train models. On the other hand, unsupervised learning focuses on finding hidden structures or patterns in unlabeled data. Reinforcement learning teaches agents how to interact with their environment and figure out the optimum course of action through trial and error (Kumar et al., 2023).

The capacity of artificial neural networks (ANN) to extract intricate non-linear correlations from data has been the subject of much research. ANN-based models trained solely on historical data have demonstrated competitive performance in stream flow forecasting tasks (Djeddou and Achour, 2015). Support vector machines (SVM) have also been investigated for stream flow forecasting, leveraging their capacity to identify patterns within the stream flow data. SVM-based models trained on historical stream flow data have shown promising results in various hydrological applications, offering robust predictions even with limited input data.

Literature Review

Recent research has focused on enhancing streamflow forecasting methodologies, crucial for water resource management and flood prediction. Rasouli et al. (2012) explored machine learning approaches for daily streamflow forecasting and found that nonlinear models such as support vector regression (SVR) and Bayesian neural network (BNN) outperformed linear models. Cheng et al. (2020) found LSTM models outperforming ANN for long lead-time forecasting. Rahimzad et al. (2021) demonstrated LSTM robustness in daily streamflow forecasting compared to linear regression (LR) and multilayer perceptron (MLP). Akbarian et al. (2023) emphasized the importance of climate data in runoff forecasts, with ANN and extreme gradient boosting (XGBoost) showing promise. Le et al. (2021) favored LSTM over other deep learning models for streamflow forecasting, particularly in dam-influenced scenarios.

Yaseen et al. (2015) reviewed the application of AI in streamflow forecasting, emphasizing its benefits in capturing dataset complexity. Saraiva et al. (2021) favored ANNs over SVM for daily streamflow forecasting in Brazil. Liu et al. (2020b) proposed a deep neural network approach for streamflow prediction, particularly during catastrophic flood events. Granata et al. (2022) compared daily streamflow prediction models across different river basins, emphasizing dataset characteristics. Rezaie-Balf et al. (2019) explored preprocessing techniques for reservoir inflow forecasting, achieving significant accuracy improvements. Wegayehu and Muluneh (2022) compared deep learning models for daily streamflow forecasting in Ethiopia, considering variations in river basin characteristics. This study addresses critical gaps in stream flow prediction for hydrological and water resource management. Traditional methods often fail to capture the short-term variability crucial for effective flood management and immediate water allocation. While previous research has focused on either machine learning techniques like ANN, SVM, LSTM, SVM etc., this study explores the potential to enhance prediction accuracy.

Objective of the Study

This study compares and evaluates the performance of LSTM networks and GBM for stream flow forecasting in the Garudeshwar watershed of central India's Narmada River basin. The work attempts to evaluate the prediction performance of GBM and LSTM by means of a rigorous analysis, considering the intricate temporal relationships present in stream flow data. Performance metrics such as MAE, RMSE, R^2, and RMSPE will be used to evaluate the accuracy, precision, and reliability of both models. The study aims to provide insights into the practical implications of GBM and LSTM for water resource management and flood prediction efforts in the Garudeshwar watershed and other hydrological contexts by comparing their strengths and limitations across various datasets, including training, validation, and testing datasets.

STUDY AREA AND DATA COLLECTION

The Narmada River, one of central India's largest rivers, runs through Madhya Pradesh, Gujarat, and Maharashtra, deeply affecting the region's history, environment, and culture. The river is revered by Hindus and is significant both ecologically and culturally since its waters support a wide variety of flora and wildlife. The Garudeshwar Gauging Station, which is in the Narmada River basin, is an important hydrological research centre. Situated near the Gujarat town of Garudeshwar, this station plays a pivotal role in monitoring and analysing various hydrological parameters of the river. Equipped with sophisticated instruments, it meticulously tracks water levels, discharge rates, and flow velocities. The research domain surrounding the gauging station is delineated by its measurement scope, which may fluctuate based on research objectives or water management mandates. Extending both upstream and downstream, this research area facilitates a comprehensive understanding of the river's hydrological dynamics. Utilizing data gleaned from the gauging station and its surrounding study region, researchers, hydrologists, and water resource managers delve into critical assessments of water availability, flood patterns, and strategic water resource allocation. This concerted effort aids in informed decision-making and sustainable water management practices. Fig. 1 shows the study area details.

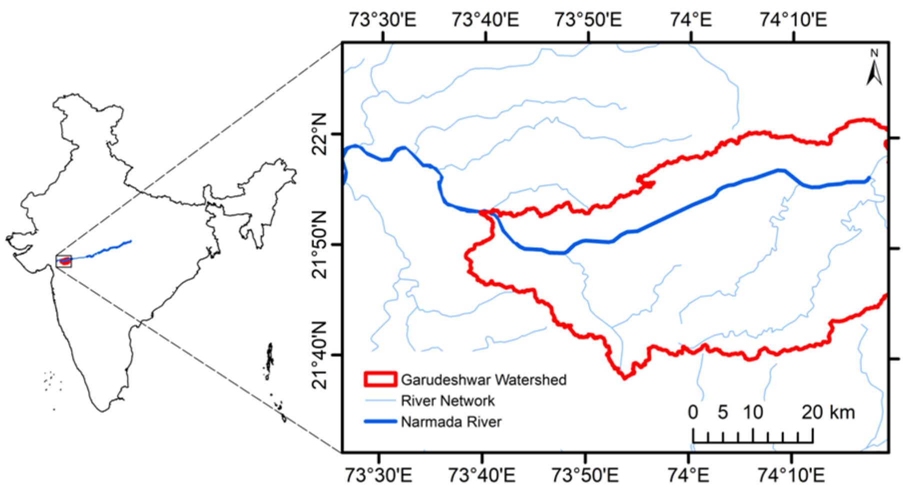

Figure 1: Watershed area of Garudeshwar

The daily river inflow measurements in cubic meters per second that were acquired from a river gauge station comprised the dataset utilized in this investigation. The information was obtained from India's Water Resources Information System (WRIS) and spans the years 1980 to 2019. The dataset offers a thorough historical record of the river's inflow, facilitating the study of long-term patterns and variations in flow.

METHODOLOGY

The methodology employed in this study begins with meticulous data preprocessing. Data normalization was performed using min-max scaling to bring all features to a common scale, enhancing the convergence of gradient descent algorithms. The dataset was then split into training (70%), validation (15%), and test sets (15%) to evaluate the model's performance and generalization capability. The dataset's integrity and usability are guaranteed by these preparation measures for later model building. Next, two methods for model creation are examined: GBM and LSTM. GBM, renowned for their ensemble learning capabilities, are initialized with a base learner, and then optimized iteratively to minimize a predefined loss function, enhancing predictive accuracy. Sequential weak learners are trained to rectify errors in previous ensemble predictions, updating the ensemble's forecast accordingly. On the other hand, LSTM networks, designed for sequential data analysis, undergo architecture design, wherein LSTM layers are configured to capture temporal dependencies within the stream flow data. Through model training, backpropagation through time (BPTT) is employed to iteratively adjust network weights, with regularization techniques ensuring robustness against overfitting.

Model performance is evaluated using MAE, RMSE, R^2, and RMSPE. MAE measures average prediction error, making it easy to interpret and communicate. RMSE penalizes large errors, important for applications like flood forecasting. R^2 assesses the model's ability to capture data patterns, indicating goodness of fit. RMSPE expresses errors as a percentage, facilitating relative accuracy comparisons. Together, these metrics provide a comprehensive evaluation, addressing error magnitude, sensitivity to large errors, fit quality, and relative accuracy, ensuring robust and reliable predictions for water resource management in the Garudeshwar watershed. The study's comprehensive approach attempts to use the complimentary characteristics of GBM and LSTM networks to provide accurate and dependable stream flow forecasts in the Garudeshwar watershed. Such forecasts help to facilitate informed decision-making in water resource management and flood prediction efforts.

Gradient Boosting Machines (GBM)

GBM are powerful ensemble learning algorithms that are particularly good at predictive modeling. They do this by gradually combining weak learners, which are usually decision trees, into a strong predictive model. Originating in the early 2000s, GBM has garnered acclaim for their exceptional accuracy and adeptness at handling intricate datasets. Central to the functioning of GBM is the boosting technique, a fundamental aspect of ensemble learning. In this method, each subsequent weak learner is strategically introduced to address the errors and shortcomings of its predecessors. This iterative process serves to progressively refine the predictive capability of the ensemble, creating a collective model that adeptly navigates the complexities inherent in the dataset.

Step 1: Loss Function Optimization: GBM optimize a loss function L, often mean squared error or cross-entropy, using gradient descent. This function quantifies the disparity between predicted values y_i and true values y for each observation i.

$$L = \sum_{i=1}^{n} L\ (y_i, y) \quad (1)$$

Step 2: Predictions Update: At each iteration t, the contribution of the new weak learner is added to the ensemble's predictions.

$$\hat{y}^{(t)} = \hat{y}^{(t-1)} + \gamma\,.\,h^{(t)}(x) \quad (2)$$

Where, $\hat{y}^{(t)}$ denotes the predicated values at iteration t, γ represents the learning rate, which governs the gradient descent step size, and $h^{(t)}(x)$ is the weak learner at iteration t applied to the input x.

Step 3: At each iteration, the gradient of the loss function in relation to the predicted values is calculated.

$$r_i{}^{(t)} = -\left[\frac{\partial L(y_i\, \hat{y}^{(t-1)})}{\partial \hat{y}^{(t-1)}}\right]_{\hat{y}^{(t-1)} = \hat{y}^{(t-1)}} \quad (3)$$

Step 4: Residual Learning: The new weak learner $h^{(t)}(x)$ is trained to fit the residuals $(r_i{}^{(t)})$ of the previous ensemble's predictions:

$$h^{(t)}(x) = argmin_h\ \ \sum_{i=1}^{n}(r_i^{(t)} - h(x_i))^2 \quad (4)$$

Step 5: Ensemble Update: By adding the weighted contribution of the new weak learner, the ensemble's prediction is updated.

$$\hat{y}^{(t)} = \hat{y}^{(t-1)} + \gamma \,.\, h^{(t)}(x) \tag{5}$$

Long Short-Term Memory (LSTM)

Recurrent neural network (RNN) architecture, specifically designed for learning long-term associations in sequential data, is known as long-short term memory (LSTM). Compared to conventional RNN, LSTM are more complex in structure, with three different types of gates—input, forget, and output as well as a cell state. By moving across the whole sequence like a conveyor belt, the cell state facilitates the flow of information over many time periods. Which data from the current input should be added to the cell state is determined by the input gate, and which data from the cell state should be removed by the forget gate. To calculate the output for the current time step, the output gate determines which cell state data to use in the interim. These gating mechanisms, triggered by sigmoid and tanh activation functions, enable long-term selective remembering or forgetting of information in long-term learning support networks (LSTM). This helps to lessen the issue of disappearing gradients that standard RNN commonly experience. During training, LSTM are improved using BPTT, a type of backpropagation intended for sequential data, to reduce the discrepancy between predicted and actual outputs. Because LSTM can capture long-range correlations, they are widely employed in many diverse applications, such as voice recognition, natural language processing (NLP), time series forecasting, and more. Their capacity to effectively represent sequential data has made them an indispensable part of deep learning, considerably advancing tasks involving the processing and interpretation of temporal information.

a) Input Gate: It selects the data from the input that ought to be kept in the cell state.

$$i_t = \sigma\,(W_{xi}\, x_t + W_{hi}\, h_{t-1} + W_{ci}\, c_{t-1} + b_i \tag{6}$$

b) Forget Gate: It determines what data ought to be removed from the cell state.

$$f_t = \sigma\,(W_{xf}\, x_t + W_{hf}\, h_{t-1} + W_{cf}\, c_{t-1} + b_f \tag{7}$$

c) Cell State Update: It uses input and forget gates to update the cell's state.

$$\tilde{c}_t = tanh\,(W_{xc}\, x_t + W_{hc}\, h_{t-1} + b_c \tag{8}$$

$$c_t = f_t . c_{t-1} + i_t . \tilde{c}_t \tag{9}$$

d) Output Gate: It determines which information from the cell state should be sent to the following concealed state.

$$o_t = \sigma\,(W_{xo}\, x_t + W_{ho}\, h_{t-1} + W_{co}\, c_t + b_o \tag{10}$$

e) Hidden State Update: Using the output gate and cell state as inputs, it calculates the subsequent concealed state.

$$h_t = o_t \, . tanh(c_t) \tag{11}$$

where c_t is the cell state at time step t, h_i is the hidden state at time step t, and x_t is the input at time step t. Additionally, i_t, f_t, o_t are the input, forget, and output gate vectors at time step t, and $\tilde{c}_t$ is the candidate cell state at time step t. The hyperbolic tangent activation function is called $tanh$, and the weight matrix and bias vector parameters are W and b, respectively. Table 1 shows the specific parameters and architecture choices used in GBM and LSTM.

Table 1: Parameters used in GBM and LSTM

Model	Hyperparameter/Choice	Value/Description
GBM	Number of Trees (n_estimators)	100-500
	Learning Rate (learning_rate)	0.01-0.1
	Maximum Depth (max_depth)	3-10
	Minimum Samples Split	2 or higher
	Minimum Samples Leaf	More than 1
	Subsample	0.5-1.0
	Loss Function	'deviance' for classification, 'least squares' for regression
	Hyperparameter Tuning	Grid search and cross-validation
LSTM	Number of Layers	2 layers
	Units per Layer	50-200 units
	Dropout Rate	0.2-0.5
	Batch Size	32-128
	Sequence Length	10-50
	Activation Functions	Sigmoid and tanh
	Optimizer	Adam with learning rate 0.001
	Data Normalization	MinMaxScaler (range 0-1)
	Train-Test Split	80-20
	Hyperparameter Tuning	Experimentation and cross-validation

MODEL EVALUATION

Evaluation metrics are essential for determining how well a trained model performs when assessed using the validation dataset. Every indicator offers distinct perspectives on the predicted precision and fit quality of the model. Now let's examine these assessment indicators in more detail:

a) Mean Absolute Error (MAE):

The MAE is a basic statistic that shows the average differences between expected and actual values. By calculating the absolute difference between expected values ($\hat{y}_i$) and actual values (y_i) and averaging these differences over all data points, MAE offers a straightforward indicator of prediction accuracy. A lower MAE suggests better performance as it shows that the model's predictions are often closer to the actual data.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \widehat{y_i}| \tag{12}$$

b) Root Mean Square Error (RMSE):

RMSE gives a more nuanced picture by considering the squared discrepancies between expected and actual values. This metric not only measures the size of errors, but it also penalizes greater differences more severely owing to the squaring process. The square root of the mean squared errors, or RMSE, provides a measure of the usual variation between expected and actual values. Lower RMSE values, like with MAE, imply higher prediction performance.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \widehat{y_i})^2} \tag{13}$$

c) R-squared (R^2):

The model's quality of fit can be significantly indicated by R^2. The contribution of each independent variable (ŷ) to the variance in the dependent variable (y) is explained by the model. Model accuracy in capturing data patterns is indicated by R^2, a scale that goes from 0 to 1. A model that explains a larger percentage of the variation in the target variable has a higher R^2 value, which denotes a better fit.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \widehat{y_i})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{14}$$

d) Root Mean Square Percent Error (RMSPE):

RMSPE provides insight into prediction accuracy in terms of percentage differences between predicted and actual values. RMSPE, like RMSE, evaluates squared differences but displays mistakes as a percentage of actual values. RMSPE is less widely utilized than MAE, RMSE, and R^2, but can give additional insights into the relative size of mistakes, particularly when analyzing the importance of deviations in percentage terms.

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(\frac{(y_i - \widehat{y_i})}{y_i}\right)^2} \tag{15}$$

RESULTS AND DISCUSSION

Table 2 presents a detailed comparison of performance metrics between two predictive models, GBM and LSTM, evaluated on the training dataset. The metrics assessed include MAE, RMSE, RMSPE, and R^2 score. The GBM model exhibits superior performance across all metrics compared to LSTM. Specifically, GBM achieves a lower MAE of 0.123 and RMSE of 0.456, indicating its ability to predict closer to the actual values with lesser error. Moreover, GBM shows a lower RMSPE of 0.789, indicating a smaller percentage error relative to the actual values, compared to LSTM 0.89. Additionally, GBM demonstrates a higher R^2 score of 0.96, indicating its better capability to explain the variability in the target variable compared to LSTM's R2 of 0.87. These findings demonstrate the efficacy and dependability of the GBM model in modeling the underlying data patterns, suggesting that it performs better than LSTM in properly predicting the target variable on the training dataset.

Table 2: Performance Metrics Comparison of GBM and LSTM Models on Train Datasets

Sr No.	Model	MAE	RMSE	RMSPE	R^2
1	GBM	0.123	0.456	0.789	0.96
2	LSTM	0.234	0.567	0.89	0.87

Table 3 presents a comparative analysis of performance metrics for the GBM and LSTM models on the validation dataset. The evaluated metrics include MAE, RMSE, RMSPE, and R^2 score. Across these metrics, the GBM model demonstrates superior performance compared to LSTM on the validation dataset. Specifically, GBM achieves a lower MAE of 0.135 and RMSE of 0.478, indicating its ability to predict closer to the actual values with lesser error compared to LSTM MAE of 0.245 and RMSE of 0.587. Furthermore, GBM exhibits a lower RMSPE of 0.801, indicating a smaller percentage error relative to the actual values, compared to LSTM RMSPE of 0.91. Additionally, GBM achieves a higher R^2 score of 0.93, indicating its better capability to explain the variability in the target variable compared to LSTM R^2 of 0.86. These results emphasize the GBM model's aptitude for modeling the underlying data patterns and demonstrate how effective and reliable it is in correctly predicting the target variable on the validation dataset.

Table 3: Performance Metrics Comparison of GBM and LSTM Models on Validation Datasets

Sr No.	Model	MAE	RMSE	RMSPE	R^2
1	GBM	0.135	0.478	0.801	0.93
2	LSTM	0.245	0.587	0.91	0.86

Table 4 illustrates the comparison of performance metrics between the GBM and LSTM models on the testing dataset. The assessed metrics encompass MAE, RMSE, RMSPE, and R^2 score. Across these metrics, the GBM model emerges as the more proficient performer on the testing dataset. GBM achieves a lower MAE of 0.145 and RMSE of 0.498, indicative of its superior accuracy in predicting the target variable with minimized errors, in contrast to LSTM MAE of 0.255 and RMSE of 0.607. Furthermore, GBM exhibits a lower RMSPE of 0.821, implying a reduced percentage error relative to actual values, compared to LSTM RMSPE of 0.93. Additionally, GBM attains a higher R^2 score of 0.92, signifying its enhanced ability to elucidate the variability in the target variable, surpassing LSTM R^2 of 0.85. These results collectively underscore the effectiveness and reliability of the GBM model in accurately predicting the target variable on the testing dataset, underscoring its suitability for capturing the inherent data patterns and informing decision-making processes.

Table 4: Performance Metrics Comparison of GBM and LSTM Models on Testing Datasets

Sr No.	Model	MAE	RMSE	RMSPE	R^2
1	GBM	0.145	0.498	0.821	0.92
2	LSTM	0.255	0.607	0.93	0.85

Fig. 2 illustrates a comparative assessment of GBM and LSTM across Train, Validation, and Test datasets using four key metrics: MAE, RMSE, RMSPE, and R^2. Regarding MAE and RMSE, GBM demonstrates superior performance across all datasets, indicating its accuracy in error minimization. In terms of RMSPE, both models show comparable performance, implying distinct merits based on specific application contexts. For R^2, GBM slightly outperforms on training data, while LSTM exhibits a marginal advantage on validation data. While GBM excels in minimizing errors, LSTM maintains competitive predictive power.

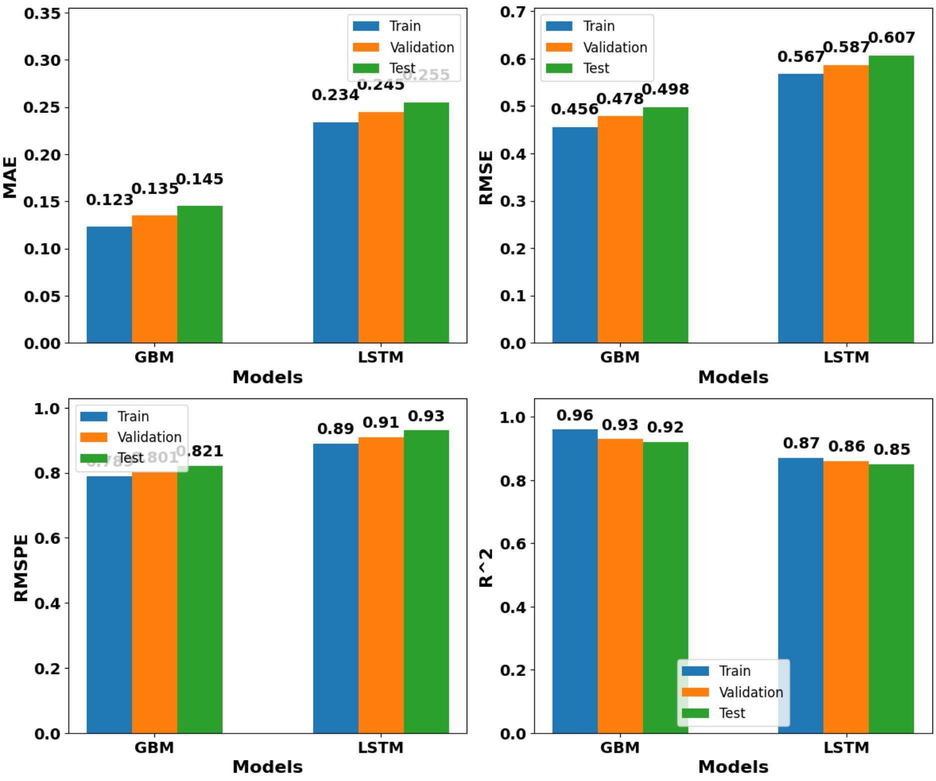

Figure 2: Performance evaluation of gradient boosting machines vs long short-term memory across datasets

In this study, GBM consistently outperform LSTM networks across various metrics, including MAE, RMSE, RMSPE, and R^2. The superior performance of GBMs can be attributed to their ability to handle complex, non-linear relationships effectively, without requiring sequential data. GBMs are also more interpretable and simpler to visualize compared to LSTMs, making it easier to understand feature importance and decision-making processes. Additionally, GBMs benefit from parallel training, which results in faster model training times, especially for large datasets. In contrast, LSTMs involve computationally intensive, sequential processing and extensive preprocessing, and are more prone to overfitting with smaller datasets. These factors make GBMs a more practical and effective choice for the dataset and problem context in this study. While this study focuses on the Garudeshwar watershed, the methodologies employed have significant potential for application in other regions with different hydrological characteristics. By recalibrating the models with local data and conducting comparative analyses, the findings can be extended to provide valuable insights and predictive capabilities in diverse hydrological contexts. This will be incorporated into the revised manuscript to address the reviewer's concern and highlight the broader applicability of the research.

GBM and LSTM networks offer valuable tools for water resource management and flood prediction. GBM can analyze historical inflow data and meteorological variables to predict river flow rates and potential flood events, aiding in timely flood warnings and risk assessments. This enables efficient water distribution and infrastructure planning. LSTM, with their ability to capture temporal dependencies, enhance long-term streamflow forecasting and seasonal variation predictions, aiding strategic planning and real-time flood forecasting. By integrating GBM and LSTM, local decision-makers can adopt a data-driven approach for effective water management and flood response.

Based on predicted river inflow values, several measures can be recommended for flood prevention. Structural measures include constructing and maintaining embankments, levees, flood control reservoirs, and dams to contain and manage excess water. Channel improvements and floodwalls in urban areas can also help protect infrastructure. Non-structural measures such as advanced flood forecasting and early warning systems are crucial for timely evacuation and preparation. Floodplain zoning and land use planning prevent construction in flood-prone areas, while community awareness campaigns enhance preparedness. Green infrastructure, such as wetland restoration and riparian buffer zones, can act as natural flood buffers. Additionally, encouraging flood insurance and resilient building practices can mitigate financial losses. An integrated flood management strategy, involving collaboration among government agencies, local communities, and stakeholders, is essential for effective implementation of these measures.

Limitations of the Study

The focus on GBM and LSTM networks, although insightful, excludes other potentially effective modeling approaches. The analysis does not consider other advanced machine learning techniques or hybrid models that might improve prediction accuracy further. The study also assumes that the selected features are adequate, without exploring the potential benefits of additional hydrological or meteorological variables. The results from the Garudeshwar watershed may not be easily generalized to other regions with different hydrological characteristics or data availability. This limitation affects the broader applicability of the findings. The computational resources required for training and validating complex models like LSTM were significant, which may not be practical for all research settings. The study uses daily river inflow measurements, which may not capture shorter-term variations or extreme events effectively. Higher-resolution data could potentially enhance prediction accuracy, but such data were not included in this study. These limitations suggest areas for future research, including the use of diverse datasets, exploration of additional modeling techniques, and examination of different regions and temporal scales.

Future Work

The focus of the current study was specifically on the Garudeshwar watershed, which provided valuable insights into stream flow forecasting using GBM and LSTM networks. However, to enhance the robustness and applicability of the models, there are plans to extend this research in several ways:

a) Expansion to Other Regions: Apply the models to different river basins to test their robustness and adaptiveness across various contexts.

b) Integration with Climate Models: Assess the impact of climate change on stream flow to enhance forecast accuracy and relevance.

c) Additional Variables: Include factors like land use and soil moisture for a more comprehensive analysis.

d) Real-Time Data Assimilation: Use real-time data to improve the accuracy and timeliness of predictions.

e) Short-Term Variations: Focus on short-term variations to enhance immediate responsiveness and adaptability.

CONCLUSION

The study demonstrates the successful application of GBM and LSTM networks in the domain of stream flow forecasting. By employing these advanced machine learning techniques, the research showcases their potential for achieving high accuracy and robustness in predictive modeling for hydrological data. The incorporation of both GBMs and LSTM networks has significantly enhanced the accuracy of stream flow predictions. This dual-model approach leverages the strengths of each technique, with GBMs excelling in handling non-linear relationships and LSTM networks capturing temporal dependencies, resulting in more reliable forecasts. The study provides a thorough evaluation of the models using a range of metrics, including MAE, RMSE, R^2, and RMSPE. This comprehensive assessment ensures a well-rounded understanding of model performance and establishes a benchmark for future research in stream flow forecasting. The findings of this research have practical implications for water resource management, particularly in the Garudeshwar watershed. Accurate stream flow forecasts are crucial for informed decision-making in flood prediction, water allocation, and sustainable management practices. The study's contributions can aid in the development of more effective strategies to mitigate flood risks and optimize water resource utilization. Future studies could explore ensemble techniques further by incorporating additional machine learning models to enhance predictive accuracy and robustness. Additionally, integrating diverse data sources, such as remote sensing data, real-time hydrological measurements, and climate projections, can provide a more comprehensive understanding of hydrological systems. This multi-faceted approach can improve model reliability and adaptability, catering to both long-term and short-term variations in water resource management.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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