Deep Learning Model (LSTM) for Streamflow Forecasting in Humber River, Newfoundland, Canada

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Report prepared by

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Summary:

Streamflow forecasting is crucial for effective water management, especially in areas vulnerable to extreme weather events like flooding and droughts. Long Short-Term Memory (LSTM) networks, a type of deep learning model, have gained prominence for their adeptness in time series forecasting tasks, including streamflow prediction. This study focuses on employing LSTM model specifically for streamflow forecasting within the Humber River basin in Newfoundland, Canada. The primary objective is to evaluate the performance of LSTM model in capturing the complex dynamics of streamflow in this region. The evaluation metrics presented in the study highlight the good performance of LSTM model, with Nash-Sutcliffe Efficiency scores consistently exceeding 0.9 across training, validation, and testing sets, indicating excellent model efficiency. Additionally, low Root Mean Squared Error and Mean Absolute Error values across all datasets demonstrate the strong predictive capabilities of the LSTM model. Furthermore, high Coefficient of Determination values indicate a high level of explained variance in streamflow predictions by the LSTM model. These findings affirm the effectiveness and reliability of LSTM model for streamflow forecasting tasks, showcasing their potential to significantly improve water management strategies.

1. Introduction:

Streamflow forecasting is essential for various water management purposes, such as flood control and drought mitigation. Traditional hydrological models face challenges in capturing the complexities of hydrological processes due to their limitations with nonlinear relationships. Deep learning models, specifically LSTM networks, have become prominent for their capability to handle long-term dependencies and nonlinear patterns in data (Feng et al., 2020).

Research has indicated that LSTM models surpass traditional hydrological models in streamflow forecasting tasks (Arsenault et al., 2023; Wi, 2022; Arsenault et al., 2022). LSTM models have exhibited superior performance in predicting streamflow in various regions, including the Humber River basin in Newfoundland, Canada (Feng et al., 2020). These models have proven effective in simulating surface runoff predictions at daily time scales (Frame et al., 2021). Furthermore, LSTM models have demonstrated greater effectiveness compared to other machine learning models like support vector machines and gradient boosting in streamflow prediction (AlDahoul, 2023).

Despite the promising results shown by LSTM models, challenges exist. The interpretability of deep learning models, including LSTMs, remains a hurdle as they are often considered "black box" models (Anderson & Radić, 2022). Additionally, the development of these models can be limited by empirical representations of physical relationships and data sparsity (Hunt et al., 2022). Nevertheless, LSTM models, especially when combined with attention mechanisms, have been recognized as powerful tools for streamflow forecasting in Canadian watersheds (Girihagama et al., 2022).

LSTM models have made significant progress in streamflow forecasting, outperforming traditional hydrological models in various studies. Their ability to capture intricate relationships in hydrological processes makes them valuable for enhancing water management strategies. However, addressing challenges related to model interpretability and data availability is crucial to further improve the application of LSTM models in streamflow forecasting.

2. Objectives

The objectives of this study are:

1. Evaluate the performance of Long Short-Term Memory (LSTM) models in streamflow forecasting within the Humber River basin in Newfoundland, Canada.
2. Assess the ability of LSTM models to capture the complex dynamics of streamflow in the study region.
3. Analyze the Nash-Sutcliffe Efficiency (NSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R2) metrics to quantify the performance of LSTM models in streamflow forecasting.

3. Methodology:

3.1 Study Area

The streamflow assessment was conducted for the Upper Humber River Watershed (UHRW) in Western Newfoundland, which is part of the Atlantic boreal region of North America. This area, specifically located in Western Newfoundland, Canada, spans approximately 2,800 square kilometers. The UHRW is characterized by its cold, dry winters, and more humid summers. Springtime snowmelt, especially pronounced in April and May, significantly raises streamflow levels, a typical pattern in areas receiving substantial winter snowfall. As the snow thaws, it augments the water volume in rivers and streams, leading to increased flow rates during these months. The annual average temperature in the region varies, with the colder months reaching lows of about -6.5°C and the warmer months highs of around 18°C. The watershed's elevation ranges from 3 to 781 meters above sea level, with Forest-Mixed and Loam being the predominant land use and soil types, respectively. A significant portion of the watershed (89%) features a medium-to-high slope gradient of 3% or greater. For a thorough understanding of streamflow simulation within the SWAT model, including the relevant functions and variables, refer to the detailed exposition provided by Islam et al. (2024).

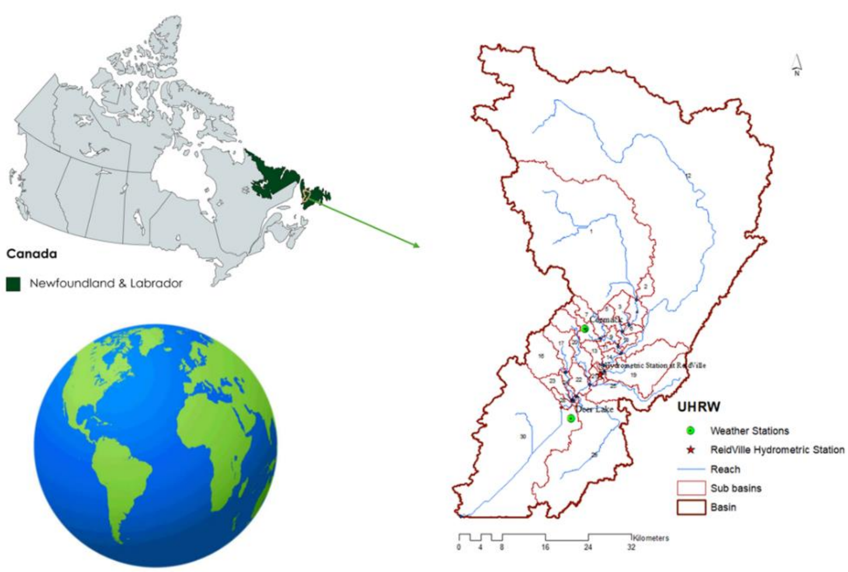

Figure 1: Study Area of LSTM Model Application.

3.2 Data Collection and Preprocessing

In the model the precipitation, temperature max an min for predictors and target is streamflow. Incorporated into the LSTM model were weather data sourced from historical records, about daily precipitation and both maximum and minimum temperatures, obtained from the Environment and Climate Change Canada's historical weather data repository, accessible at https://climate.weather.gc.ca/historical_data. Dataset was compiled from two distinct weather station Cormack spanning the extensive time frame from 1982 to 2022.

Humber River discharge data are necessary for calibrating and validating the model in the research area. The discharge was collected at the hydrometric station along the Humber River: Reidville. The gauged station data were used to calibrate and validate the model. The calibrated model can then predict the river discharge in the study area. Daily river discharge data were obtained from the Environment and Natural Resources, Canada (https://wateroffice.ec.gc.ca/), from 1982 to 2022.

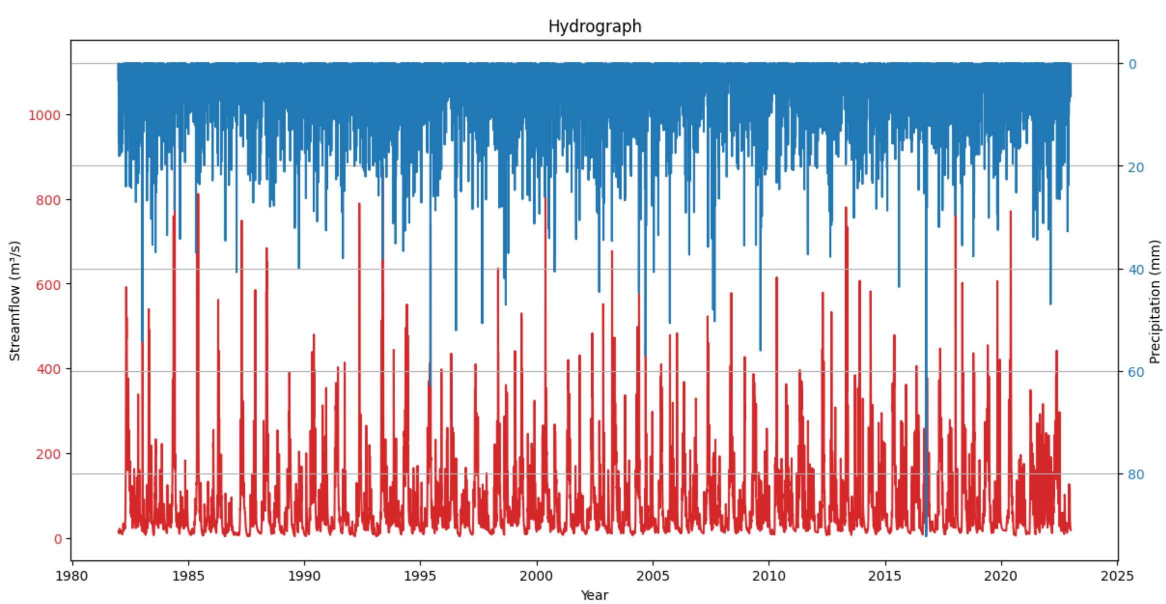

Figure 2: Upper Humber River Flow (m³/s) and Precipitation (mm) Hydrograph,1982-2022.

3.3 Data Preprocessing

The streamflow and meteorological data collected from 1982 to 2022 were stored in an Excel file for further analysis. Before feeding the data into the model, a preprocessing step was conducted to ensure its quality and compatibility with the LSTM model. This preprocessing involved several key tasks. Firstly, missing values within the dataset were handled using appropriate techniques, such as interpolation or imputation, to maintain the integrity of the data. Secondly, the variables were normalized to a common scale to prevent biases and ensure equal importance during model training. Lastly, the data was formatted into suitable input-output sequences, considering the temporal nature of the data, to enable the LSTM model to learn and predict streamflow values effectively. By undergoing these preprocessing steps, the data was optimized for training the model, improving its accuracy and performance in streamflow prediction tasks.

3.4 LSTM architecture

The architecture of the LSTM model consists of multiple layers designed to process and predict streamflow data effectively. The model starts with an input layer that receives weather data and streamflow records. Following the input layer, several LSTM layers are stacked to capture temporal dependencies and patterns within the time-series data. Each LSTM layer is equipped with memory cells that retain information over long sequences, allowing the model to learn intricate relationships between past and future values. The final LSTM layer outputs the processed data to a dense (fully connected) layer, which performs the final prediction of streamflow values. Throughout the architecture, dropout layers are interspersed to prevent overfitting by randomly deactivating a fraction of neurons during training. This layered approach ensures that the model can generalize well and make accurate predictions across various data subsets.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_4 (LSTM)               (None, 64)                16896

 dense_8 (Dense)             (None, 8)                 520

 dense_9 (Dense)             (None, 1)                 9

=================================================================
Total params: 17425 (68.07 KB)
Trainable params: 17425 (68.07 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
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The LSTM model summary provides a detailed overview of the architecture and parameters of the model (Figure 3). It consists of three main layers: an LSTM layer (lstm_4) with an output shape of (None, 64), a dense layer (dense_8) with an output shape of (None, 8), and another dense layer (dense_9) with an output shape of (None, 1). The LSTM layer has 16,896 parameters, the dense layer has 520 parameters, and the final dense layer has 9 parameters, totaling 17,425 parameters in the model. All parameters are trainable, contributing to the model's ability to learn and make predictions based on the input data. The total size of the model parameters is 68.07 KB, with no non-trainable parameters, indicating that the entire model is optimized for learning and inference tasks related to streamflow prediction.

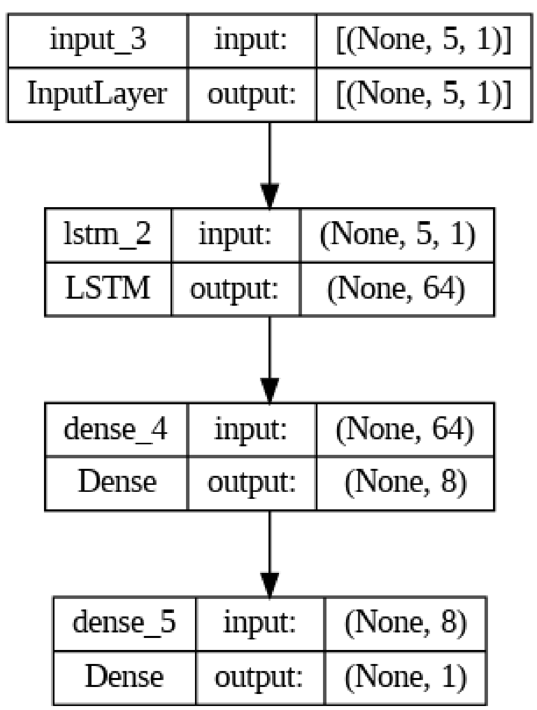

Figure 3: LSTM Model Layers Architecture

3.5 Model Training and Evaluation

The model training and evaluation process began with splitting the dataset into three subsets: training, validation, and testing. The LSTM model was trained using the historical data from the training set, allowing it to learn patterns and relationships within the streamflow and meteorological variables. During training, hyperparameters such as learning rate, batch size, and number of epochs were fine-tuned using the validation set to optimize the model's performance and prevent overfitting. Once the model was trained, it was evaluated on the testing set to assess its predictive capabilities and generalization to unseen data. Evaluation metrics such as mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R-squared) were calculated to measure the model's accuracy, reliability, and ability to capture the variability in streamflow data. This rigorous training and evaluation process ensured that the LSTM model was robust, effective, and capable of making accurate predictions for streamflow forecasting.

4. Results:

The data file is structured as a pandas Data Frame with a Date time Index, spanning from January 1, 1982, to December 31, 2022, comprising 14975 entries. It contains four columns:

- Date: Representing the date with a datetime data type.
- Temp_mean: Showing the mean temperature, stored as float64 data type.
- PPT: Denoting precipitation, stored as float64 data type.
- Streamflow: Indicating the streamflow, also stored as float64 data type.

The non-null count for all columns is 14975, indicating that there are no missing values in the dataset. The memory usage of the Data Frame is approximately 585.0 KB. This dataset is well-structured for analyzing temporal patterns and relationships between temperature, precipitation, and streamflow over the specified time.

The performance of the LSTM model was evaluated. The LSTM model demonstrated good performance in terms of forecasting accuracy and ability to capture the complex dynamics of streamflow in the Humber River basin. The results suggest that deep learning models, particularly LSTMs, hold great potential for improving streamflow forecasting in the region.

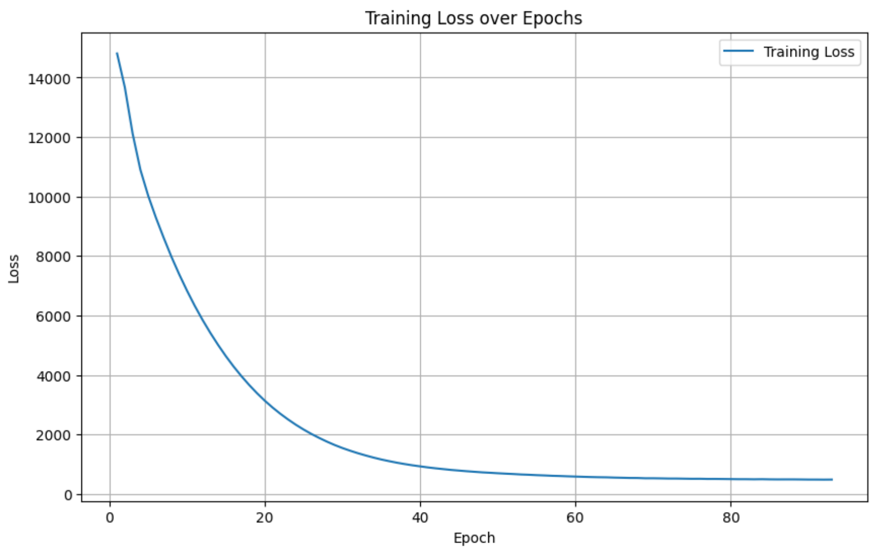

Figure 4: LSTM Model Layers Architecture

Figure 4 illustrates the loss reduction over epochs. Initially, the loss starts at 15,000 and experiences a sharp decline until reaching approximately 30 epochs. After this point, the loss continues to decrease more gradually, eventually plateauing around 80 epochs.

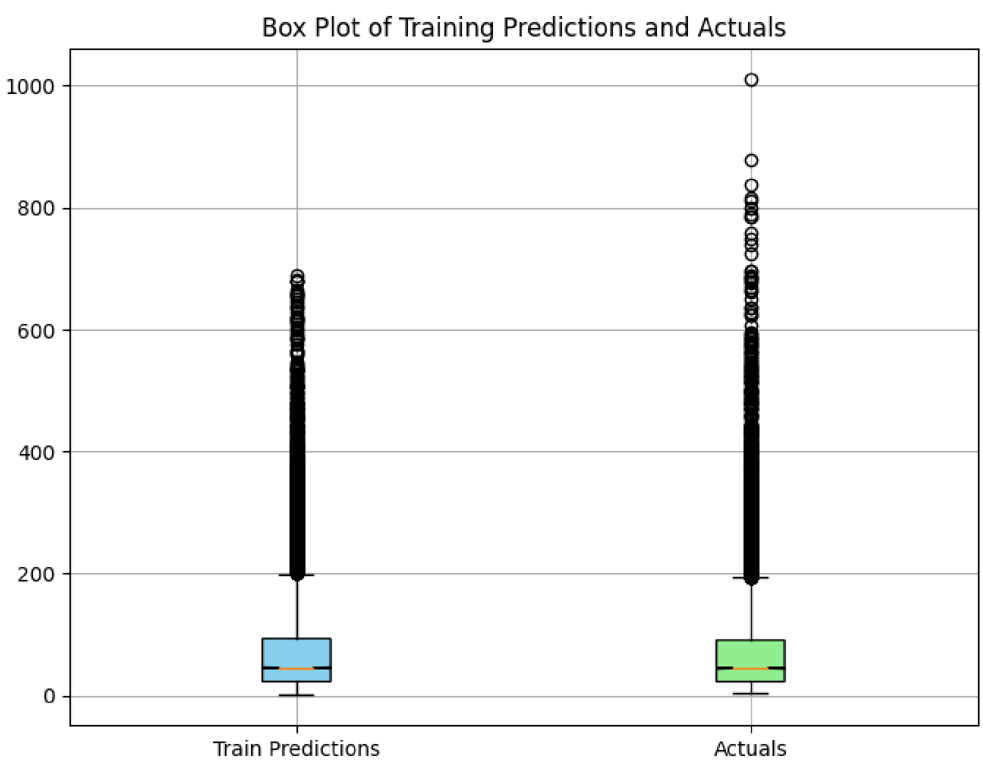

Figure 5: Box plot comparing the actual flow values with the predicted flow values.

Figure 5 illustrates a five-number summary box plot comparing the actual flow values with the predicted flow values. The five-number summary for the train predictions shows a mean of 77.25, standard deviation of 90.17, minimum value of 1.17, first quartile at 22.59, median at 45.29, third quartile at 93.53, and maximum value of 688.63. On the other hand, the Five-number summary for the Actuals indicates a mean of 77.92, standard deviation of 94.96, minimum value of 3.70, first quartile at 22.50, median at 44.60, third quartile at 90.82, and maximum value of 1010.00. This comparison visually represents the distribution and variation between the predicted and actual flow values, providing insights into the model's performance in streamflow forecasting.

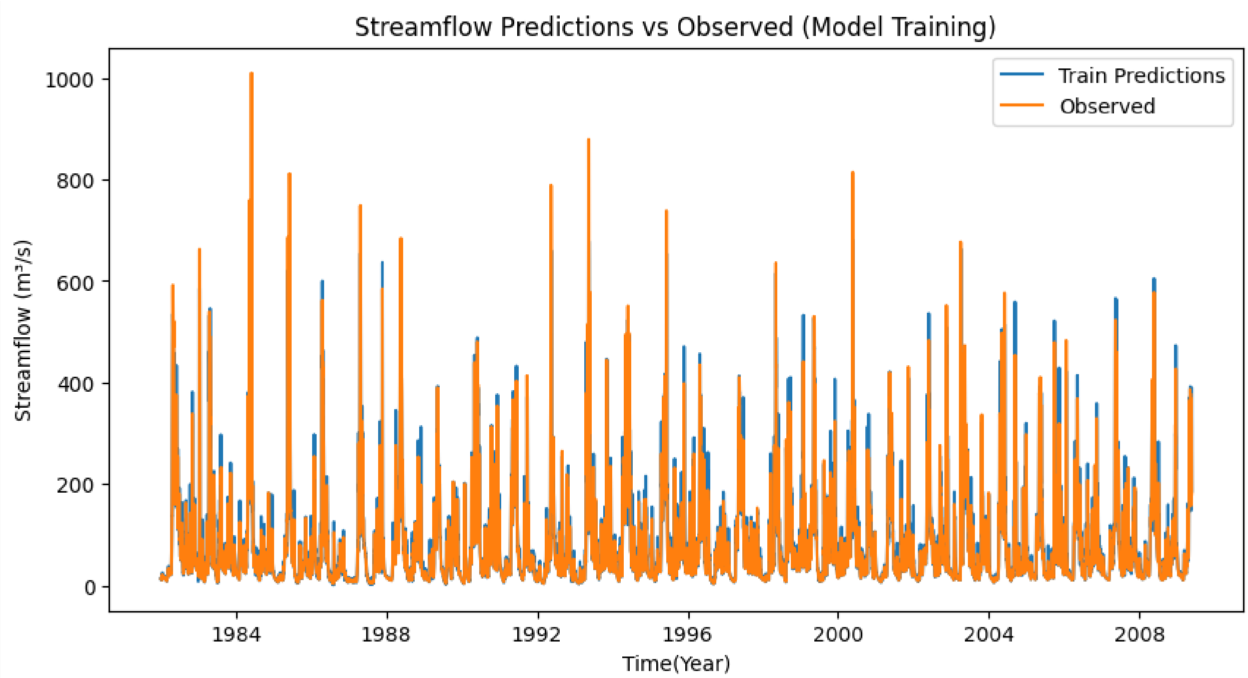

Figure 6: Comparison between streamflow predictions and observed values during model training.

Figure 6 depicts the comparison between streamflow predictions and observed values during the model training phase. The training data provides insights into the historical trends of temperature, precipitation, and streamflow in the Humber River basin from 1982 to 2008. The data indicates that the mean temperature during this period was approximately 2.70°C, with fluctuations ranging from a minimum of -26.01°C to a maximum of 23.05°C. Precipitation levels varied widely, with a mean of 3.27 mm and a maximum of 62.85 mm. Streamflow ranged from a minimum of 3.70 m^3/s to a maximum of 1010 m^3/s, with a mean flow of 77.72 m^3/s, reflecting the significant variability in hydrological conditions over the years.

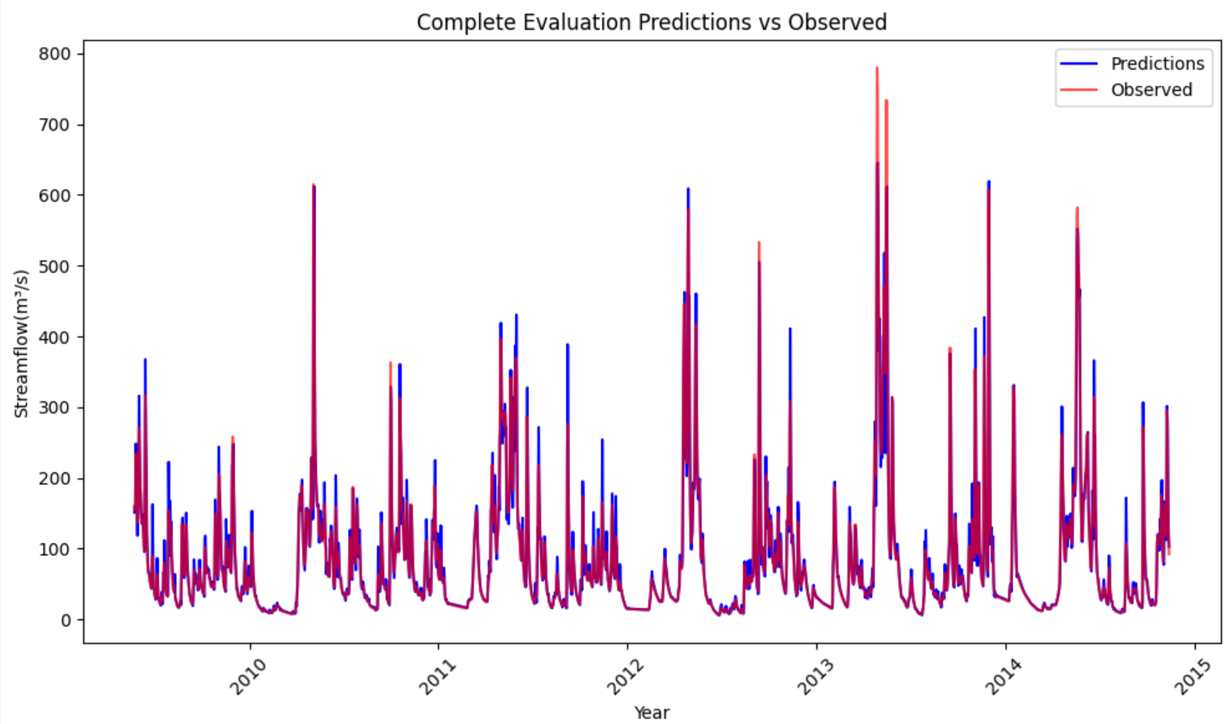

Figure 7: Comparison between streamflow predictions and observed values during model evaluation.

Figure 7 depicts the comparison between streamflow predictions and observed values during the model evaluation phase. The evaluation phase from 2009 to 2014, similar trends in temperature, precipitation, and streamflow are observed. The mean temperature during this evaluation period was approximately 3.74°C, slightly higher than in the training dataset. Precipitation levels remained consistent, with a mean of 3.16 mm, indicating relatively stable precipitation patterns. Streamflow values ranged from 6.48 m^3/s to 780 m^3/s, with a mean flow of 83.02 m^3/s. These findings suggest a continuation of the hydrological patterns observed in the training data, albeit with some variations over time. The model under predicted values in 2013 but low flow prediction quite good.

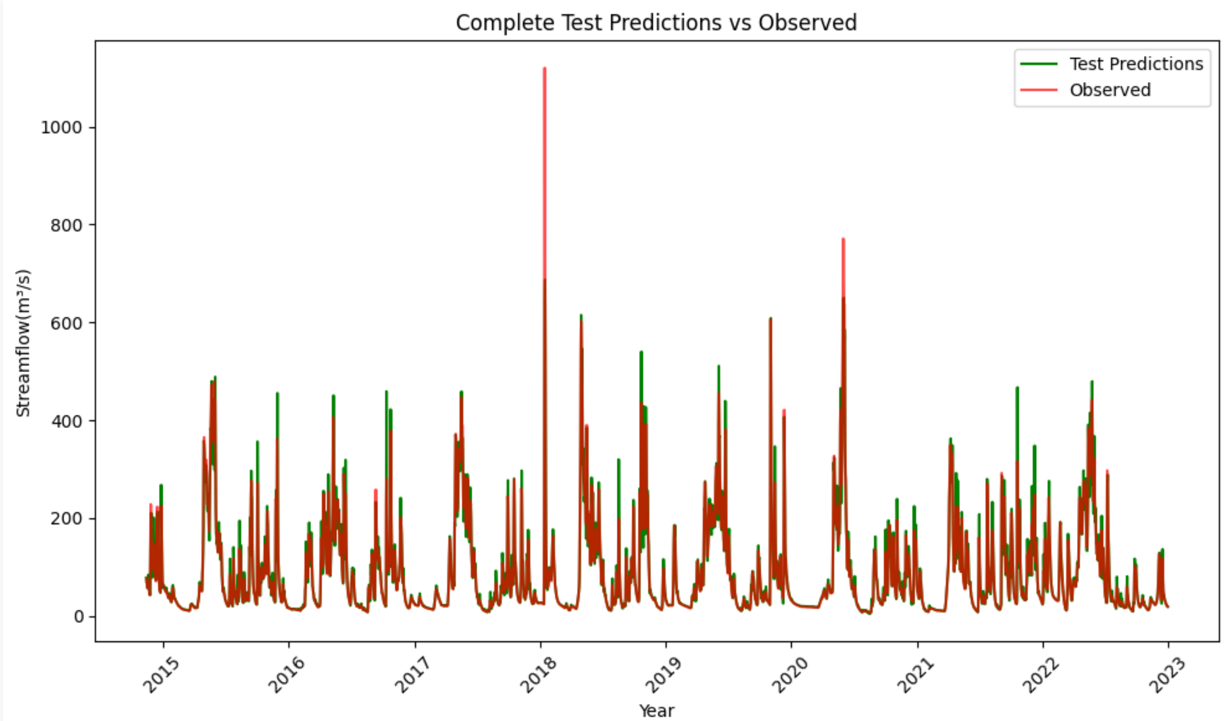

Figure 8: Comparison between streamflow predictions and observed values during model test.

Figure 8 depicts the comparison between streamflow predictions and observed values during the model training phase. The test data summary, covering the period from 2015 to 2022, shows further trends in temperature, precipitation, and streamflow. The mean temperature during this period was 3.22°C, similar to the evaluation dataset. Precipitation levels exhibited variability, with a mean of 3.33 mm and a maximum of 92.24 mm. Streamflow values ranged from 5.56 m3/s to 1120 m3/s, with a mean flow of 86.47 m3/s. These results indicate ongoing fluctuations in hydrological conditions, highlighting the importance of robust forecasting models to capture and predict such variability for effective water resource management. The model underestimated high flows in 2018 and slightly overestimated them in 2016, 2017, 2019, and 2022.

Table 1: LSTM Model Evaluation Metrics

Evaluation Metrics	Training	Validation	Test
Nash-Sutcliffe Efficiency (NSE)	0.95	0.93	0.93
Root Mean Squared Error (RMSE)	20.91	24.22	24.42
Mean Absolute Error (MAE)	8.60	10.21	9.68
Coefficient of Determination (R^2)	0.95	0.93	0.93

The evaluation metrics presented in Table 1 demonstrate the robustness and accuracy of the LSTM model in predicting streamflow for the Humber River. The NSE values of 0.95 for training, 0.93 for validation, and 0.93 for test sets indicate a high level of predictive accuracy, suggesting that the model closely replicates the observed data. The RMSE values, while slightly higher in the validation (24.22) and test (24.42) sets compared to the training set (20.91), remain reasonably low, confirming the model's ability to generalize well to unseen data. The MAE values also exhibit a similar pattern, with minor increases from training (8.60) to validation (10.21) and test (9.68) sets, further emphasizing the model's reliable performance across different data subsets. Finally, the R^2 values mirror the NSE results, with consistent scores of 0.95 for training and 0.93 for both validation and test sets, reinforcing the model's strong predictive capability and its effectiveness in capturing the variance within the dataset. Overall, these metrics collectively indicate that the LSTM model is well-calibrated and proficient in forecasting streamflow in the Humber River watershed.

6. Conclusion:

This study showcases the effectiveness of Long Short-Term Memory (LSTM) models in streamflow forecasting within the Humber River basin in Newfoundland, Canada. The findings underscore the potential of deep learning methodologies in enhancing the accuracy and reliability of hydrological forecasting. However, despite their robust predictive abilities, LSTM models encounter certain limitations, such as the necessity for extensive historical data, substantial computational resources, and limited interpretability. Future research endeavors should focus on addressing these constraints by exploring hybrid model approaches, integrating real-time data inputs, enhancing model interpretability, and broadening the research scope to encompass various geographic regions and climatic conditions. Moreover, future research could involve the integration of real-time data from websites or sensor measurements into the model for real-time forecasting of streamflow, soil moisture, and other hydrological variables. Leveraging these advancements would empower water resource managers to make more informed decisions, thereby mitigating the impacts of floods and droughts. Ultimately, these efforts contribute to more effective water resource management and planning, ensuring the sustainable utilization of water resources for present and future generations.

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