Title page:

Efficient Performance Evaluation of Long Short-Term Memory and Recurrent Neural Network in Prediction of Water Inundation Frequency.

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ABSTRACT

Aim:The primary objective of this research is to ascertain how well Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) predict the frequency of flooding, one of the most dangerous natural disasters that can seriously harm infrastructure and property. **Materials and Methods:** There are two sets of suggested algorithms. A comparison is made between Recurrent Neural Networks and Long Short-Term Memory. Both systems are capable of accurately forecasting the frequency of a water inundation. The frequency of water inundations is examined for accuracy. Future water inundation episodes must be predicted, and Long Short-Term Memory's capacity to manage long-term dependencies and Recurrent Neural Networks s' capacity to spot patterns and trends in sequential data are essential. The algorithm builds a model based on the characteristics of the training set of data, which it then applies to determine the value of fresh data. Water inundation frequency is recognized using the Long Short-Term Memory and Recurrent Neural Network of sample size (N=20) methods. Using SPSS, the significance value of the data set was estimated with a G-power value more than 80%. **Results:** Long Short-Term Memory has obtained an accuracy of 93.0095% which is comparatively higher than RNN with an accuracy of 87.0345%. There is a significant difference between the two groups with a significance value of 0.019($p<0.05$).**Conclusion:** In conclusion, these results show that the Long Short-Term Memory has a higher predictive capacity for estimating the frequency of flooding.Long Short-Term Memory outperforms RNN for applications that need to capture long-term dependencies in the data.

Keywords : Deep Learning, Floods, Long Short-Term Memory,Machine Learning, Natural Catastrophes, Neural Networks, Recurrent Neural Network, Water Inundation Frequency.

INTRODUCTION

Water inundation, a phenomenon that is of great importance nowadays, is the overflowing or submergence of land as a result of a variety of events, including floods, storm surges, and severe rainfall. This phenomenon has serious implications for the environment and the economy, endangering both human settlements and natural ecosystems(Bates 2023). Floods are a symptom of water inundation that worsen the effects by submerging significant regions, damaging infrastructure, uprooting communities, and interfering with daily life.Accurate prediction models are desperately needed to reduce possible damages since floods, in particular, are becoming more frequent and unpredictable(England et al. 2019). As we explore the complexities of this problem, it becomes clear that resilient urban planning and efficient disaster management for Natural Catastrophes depend on an improved knowledge and forecast of water inundation events, such as floods(Siahkamari et al. 2018).

The seriousness of the problem is highlighted by the statistical study of flood episodes. The magnitude of damage caused by Natural Catastrophes is graphically represented in Figure 1(Cho et al. 2022), which highlights the increasing impact during two notable decades, from 1980 to 1999 and 2000 to 2019. In our quest to comprehend the state of the field, a thorough search of the Scopus database produced 2,801 publications on Science Direct and more than 17,700 articles on Google Scholar in the last five years, demonstrating the growing interest among academics in the field of water inundation prediction. This flood is a complex issue that threatens not just the nearby environment but also agriculture, public safety, and the stability of the socioeconomic system as a whole(Mosavi, Ozturk, and Chau 2018).One of the most important areas that is being investigated to reduce damage to nature and towns and cities is the flow of streams forecasting, which was caused by Natural Catastrophes(Anaraki et al. 2020).The inundation of marshes and floodplains is also essential to the functioning of the Earth system(Costache 2019). The worldwide pattern of the flow of energy, nutrients, and water to the coastal ocean are governed by the floodplain's capacity to dramatically reduce river waves(Brunner et al. 2021).

This project's main goal is to carry out an effective performance evaluation of RNN and LSTM in terms of water inundation frequency prediction. The Investigation goal is to increase the predicted accuracy and dependability of models by utilizing deep learning (DL) techniques, which will help with early warning systems and better preparedness for Natural Catastrophes. Furthermore, this research aims to investigate the complex dynamics of flooding and Natural Catastrophes, taking into account variables including urbanization, land-use patterns, and climate change(Le et al. 2019). By exploring these intricacies, the investigation goal is to create reliable models that not only yield precise forecasts but also furnish significant perspectives for anticipatory decision-making concerning the growing risks of flooding(Kim and Kim 2020).

MATERIALS AND METHODS

This study was carried out in the Saveetha Institute of Medical and Technical Sciences' Data Analytics laboratory. A highly configurable system in the lab enables detailed investigation and accurate outcomes. Ten respondents in total were included in the study, and they were split into two groups: Group 1 used the LSTM(Long Short-Term Memory) method and Group 2 used the RNN(Recurrent Neural Network). With an 80 percent G-Power value, the study's statistical power was maintained at a power level of 0.8 (beta) and a significance level of 0.05 (alpha). In addition, a 95 percent confidence interval was maintained in order to systematically compute and evaluate the differences between the two groups.

The "Kerala Floods" database(Devakumar 2019) is utilized in this water inundation occurrence prediction. The dataset is organized as comma-separated values (CSV).The dataset includes characteristics that increase the accuracy of frequency perseverance, such as year, months, and yearly rainfall. The dataset has been cleaned to make training and testing easier. Standardization was applied to the data, missing values were eliminated, and null values were replaced with averages or medians. The preprocessed, feature-rich dataset is given to the LSTM algorithm.

The method presented in this study was applied to a specific dataset, and the outcomes were contrasted with the well-known RNN algorithm. The dataset is set up in this case as a comma-separated value (CSV) file, which holds a range of data values. To perform an exhaustive examination and comparison, the dataset was subjected to a comprehensive analysis of the records using the algorithms presented in this research. The gear setup for this work was an Intel dual-core processor with 8 GB of RAM. Utilizing Jupyter Notebook, Python, and a MySQL database, the software configuration offered a stable platform for executing the algorithm and doing the comparative analysis.

Long Short-Term Memory

A specialized kind of recurrent neural network (RNN) called LSTM was created to solve the vanishing gradient problem, which plagues many RNNs in the conventional sense. Time-series prediction challenges like water inundation frequency are a good fit for LSTMs because of their shown effectiveness in modeling sequential data during Natural Catastrophes(Liu et al. 2020). Their capacity to recognize long-term dependencies in the material, which enables them to retain pertinent knowledge over time, is their primary characteristic. In order to control the information flow and allow the model to selectively retain or discard data at each time step, LSTMs employ a memory cell along with three gates: input, forget, and output(Yan et al. 2021). This feature enables LSTMs to learn complex patterns from time-series data, which enhances their ability to estimate the frequency of water inundations.

Recurrent neural network

The analysis of time series can benefit from the application of RNNs, a kind of neural networks created for sequential data processing. The vanishing gradient problem, on the other hand, hinders the ability of conventional RNNs to capture long-range dependencies in sequences(Bowes et al. 2019). RNNs may find it difficult to remember pertinent information over long stretches of time when it comes to forecasting the frequency of water inundations. They are able to learn temporal patterns, but the difficulties with the vanishing gradient may make them less effective(Asanjan et al. 2018). RNNs are less effective for jobs that require modeling long-term dependencies in time-series data because they lack specialized techniques to solve this problem, in contrast to LSTMs.

Statistical Analysis

IBM SPSS version 26 was used for the analysis, and 20 samples were used for the RNN (Recurrent Neural Network) and LSTM (Long Short-Term Memory) methods within the defined Groups 1 and 2. The analysis's accuracy values were evaluated in SPSS, with an emphasis on how the model was trained utilizing the attributes of the dataset. In order to compare the two algorithms' performances, T-Tests were calculated for each epoch. This statistical technique made it easier to assess the algorithms' accuracy values rigorously and gave important information about how each performed during training.

RESULTS

Table 3 shows the accuracy numbers for both Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) that were obtained from the raw data table. Both LSTM and RNN were used to calculate accuracy figures with sample sizes of 20. Table 3 shows that the RNN method attained an accuracy of 87.0345%, but the mean accuracy for the LSTM algorithm is 93.0095%. These findings imply that the suggested LSTM method performs more accurately than other algorithms. The LSTM approach was selected for this investigation instead of RNN, highlighting its better performance throughout the analysis.

Assuming equal variances, Table 5 reports an "F" value of 6.008 and a corresponding "Sig" value of 0.019. As shown in Table 5, the 95% confidence intervals for the difference under the assumptions of equal and unequal variances are 4.01291 to 3.99868 for the lower case and 7.93709 to 7.95132 for the upper case. The resulting bar graph in Figure 2 clearly shows that the accuracy of LSTM (Long Short-Term Memory) is significantly higher than that of RNN (Recurrent Neural Network), when the mean accuracy is plotted on the Y-axis against the groups on the X-axis.

DISCUSSION

The study's acquired significance value, which is 0.019 (two-tailed, $p>0.05$), shows that LSTM (Long Short-Term Memory) performs better in the regions under investigation than RNN (Recurrent Neural Network). The LSTM algorithm outperforms the RNN (Recurrent Neural Network) with a mean accuracy of 93.0095%, according to the mean accuracy study. The RNN's mean accuracy is 87.0345%. This implies that LSTM outperforms RNN when compared directly.

Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) are two reliable approaches, each with unique advantages and disadvantages. Prominent for its skill in representing long-term dependencies in sequential data, LSTM performs exceptionally well in time series forecasting and natural language processing, among other applications. Its capacity to store complicated temporal correlations selectively is improved by its gating mechanism(Kim and Han 2020). However, the computing needs and training complexity of LSTM can provide difficulties. RNN, on the other hand, is particularly well-suited for modeling sequential data, particularly in time series applications, due to its exceptional computational efficiency and efficacy in handling nonlinear interactions(Wan et al. 2019). For smaller or less complicated datasets, its training method simplicity is appealing. It is imperative to take into account the heightened vulnerability of RNN to overfitting, as well as its restricted ability to capture extended dependencies within the data.

The dataset's size, diversity, and feature selection, as well as uncertainties regarding generalizability and untested algorithmic alternatives, could all pose possible limitations to the study. Future study should prioritize expanding datasets to include a wider range of sources in order to estimate water inundation frequency more thoroughly. This will help to overcome these limitations and advance the subject. Prioritizing ensemble models, interpretability, and real-world applications in environmental science and crisis management can improve prediction accuracy and comprehension of Water Inundation Frequency(DeVries et al. 2017). The development of more potent predictive models may be facilitated by further investigation into various machine learning and deep learning techniques, parametric optimization, and validation in practical settings.

CONCLUSION

In conclusion, the study's main objective was to estimate the frequency of water inundations using the LSTM (Long Short-Term Memory) method. The RNN (Recurrent Neural Network) model achieved a mean accuracy of 87.0345%, while the LSTM algorithm achieved a mean accuracy of 93.0095%. The study methodically investigated how well LSTM and RNN performed in this predicting task, and it produced some interesting findings. Both models functioned satisfactorily, although LSTM performed more accurately than RNN. Given its sensitivity to past hydrological patterns, LSTM's ability to capture long-term dependencies in time series data emerged as a critical advantage in water inundation frequency prediction. RNN performed competently overall, however it was less successful at capturing complex temporal correlations. As a result, the research comes to the conclusion that LSTM is a superior option for forecasting the frequency of water inundations because of its sophisticated capacity to handle sequential data and account for long-term relationships.

DECLARATION

Conflict of Interests

This paper contains no declared conflicts of interest. To maintain our commitment to academic integrity and prevent any inadvertent participation with concerns related to academic dishonesty, we carefully checked that our work is original.

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Authors Contribution

Author KSG actively participated in the data synthesis, analysis, and gathering. On the other hand, Author SKA made a significant contribution to the research proposal, verified the data, and offered critical criticism throughout the paper review procedure.

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TABLES AND FIGURES

Table 1. Representing LSTM (Long Short-Term Memory) algorithm pseudocode**.**

Input: Kerala floods data
Output: Prediction of Water Inundation Frequency
Stage 1: Data Collection and Preprocessing Dataset Source: The Kerala floods dataset's raw data was extracted. Processed Outcome: A dataset that has been specially selected and tailored for the study on floods in Kerala. Overview of Data Transformation: The goal is to collect and preprocess the Kerala floods dataset, which includes filling in any missing values and converting the information into a format that can be used for time-series analysis. This procedure can entail enhancing the quality of satellite imagery data, incorporating thorough meteorological records, and making sure the dataset encompasses the pertinent timeframes related to the floods in Kerala.
Stage 2: Determining Features: Data Ingestion: Following preparation, Kerala floods the data. The result produced was a distillation of key characteristics specifically designed for LSTM modeling. Task Overview: Identify key elements that could be used to forecast Kerala floods, possibly including information on river levels, rainfall, land cover, and past flood incidents.
Stage 3: Data Partitioning: Data Input: Features identified from Kerala floods data. Outcome Generated: Separation into training and testing datasets. Task Overview: Divide the processed Kerala floods data into training and testing sets, ensuring consideration for the temporal aspect to enable effective generalization to future flood occurrences.
Stage 4: Model Choice: Model Input: LSTM architecture. Outcome Generated: Configured LSTM model for predicting Kerala floods. Task Overview: Opt for the LSTM model due to its adeptness in capturing sequential dependencies in time-series data, a crucial factor for predicting the frequency of floods in Kerala over time.

Stage 5: Model Training: Training Data Input: Training data and chosen features from Kerala floods. Outcome Generated: Trained LSTM model tailored for Kerala floods. Task Overview: Train the LSTM model using selected features and historical data specific to Kerala floods. Adjust LSTM parameters to effectively capture temporal patterns in the dataset.
Stage 6: Model Assessment: Trained Model Input: Trained LSTM model and testing data for Kerala floods. Outcome Generated: Performance metrics indicating the LSTM model's effectiveness for Kerala floods. Task Overview: Assess the LSTM model's performance on the testing dataset from Kerala floods, considering factors such as prediction accuracy, sensitivity to flood events, and robustness in capturing temporal patterns.
Stage 7: Model Insight: Trained Model Input: Trained LSTM model for Kerala floods. Outcome Generated: Understanding LSTM model behavior insights for Kerala floods. Task Overview: Explore the interpretability of the LSTM model specifically concerning Kerala floods. Understand how the model utilizes historical information to predict flooding events in the region.
Stage 8: Implementation: Model Deployment Input: Trained LSTM model and selected features for Kerala floods. Outcome Generated: Deployed LSTM model for predicting floods in Kerala. Task Overview: Deploy the trained LSTM model for predicting floods in Kerala in a real-world setting. This may involve integrating the model into a system capable of providing timely flood predictions for decision-makers in the region.

Table 2. Representing RNN (Recurrent Neural Network) algorithm pseudocode.

Input: Kerala floods data
Output: Prediction of Water Inundation Frequency
Stage 1: Obtaining and Transforming Data Preliminary Dataset: Unprocessed data taken from the Kerala floods dataset. Processed Outcome: Modified dataset created especially for the flood research in Kerala. Synopsis: Get the Kerala floods dataset, handle missing values, and arrange the data in a way that makes it appropriate for time-series analysis. This could entail enhancing meteorological records, fine-tuning satellite imagery data, and making sure the information includes pertinent flood times.
Stage 2: Characteristic Recognition Source of Processed Data: Data about the floods in Kerala. Feature Selection Outcome: a distilled list of essential characteristics for LSTM modeling. Synopsis: Identify key elements for forecasting flooding in Kerala, maybe including variables such as historical flood records, river levels, land cover, and rainfall data.
Stage 3: Distribution of Data Data from the floods in Kerala was used to choose the features. Training and Testing Sets as a Result: Partitioned datasets for testing and training models. Synopsis: To ensure effective generalization to future flood occurrences, divide the processed data from the Kerala floods into training and testing sets, taking into account the temporal component.
Stage 4: Choose a Model Model of Choice: RNN architecture. Result of Model Configuration: RNN model configured. Synopsis: Because the RNN model is so good at simulating sequential dependencies in time-series data, choose it. RNNs can be used to estimate the frequency of water inundations since they are appropriate for tasks where past data has a major impact on future outcomes.
Stage 5: Model Training Training Data Source: Training data and selected features. Resulting Trained Model: Refined RNN model through training.

Overview: Train the RNN model using selected features and historical data, adjusting RNN parameters to effectively capture sequential patterns in the context of water inundation frequency prediction.
Stage 6: Model Assessment Trained Model and Testing Data Source: Trained RNN model and testing data. Performance Metrics Outcome: Metrics assessing the RNN Model's performance. Overview: Evaluate the RNN model's capability to predict water inundation frequency accurately on the testing dataset, comparing its performance metrics with those of the LSTM model.
Stage 7: Model Interpretation Trained Model Source: Trained RNN model. Insights into Model Behavior: Understanding RNN model behavior. Overview: Examine the interpretability of the RNN model, gaining insights into how it processes sequential information and selected features to predict water inundation frequency.
Stage 8: Model Implementation Trained Model and Feature Source: Trained RNN model and selected features. Deployed Model Result: Implemented RNN model for predicting water inundation frequency. Overview: Deploy the trained RNN model in a real-world setting, offering efficient predictions of water inundation frequency. Ensure smooth integration for practical applications and compare its deployment considerations with those of the LSTM model.

Table 3. Representing the Accuracy(93.005%) of LSTM & Accuracy(87.0345%) of RNN Algorithms. The RBFNN Algorithm is less accurate than the LSTM Algorithm

SAMPLE NO	LSTM(%)	RNN(%)
1	96.81	92.62
2	96.25	92.55
3	95.89	91.67
4	95.74	91.49
5	94.78	90.43
6	94.68	89.36
7	94.45	88.92
8	94.32	88.34
9	92.56	87.96
10	92.55	87.82
11	92.41	87.23
12	91.37	86.17
13	92.31	85.69
14	91.63	85.11
15	91.49	84.24
16	91.34	84.04
17	91.14	82.33
18	90.85	81.96
19	89.67	81.91
20	88.95	80.85
AVERAGE	93.0095	87.0345

Table 4. Group Statistics Results-LSTM has a mean accuracy (93.0095%), St. Deviation (2.23460), whereas RNN has a mean accuracy (87.0345%), St. Deviation (3.71408).

	Group	N	Mean	Std. Deviation	Std. Error Mean
Accuracy	LSTM	20	93.0095	2.23460	0.49967
	RNN	20	87.0345	3.71408	0.83049

Table 5. The independent sample t-test for Equality of Means is given with the Equal variances assumed and also Equal variances not assumed.

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Accuracy	Equal variances assumed	6.008	0.019	6.165	38	0.000	5.97500	0.96922	4.01291	7.93709
	Equal variances not assumed			6.165	31.162	0.000	5.97500	0.96922	3.99868	7.95132

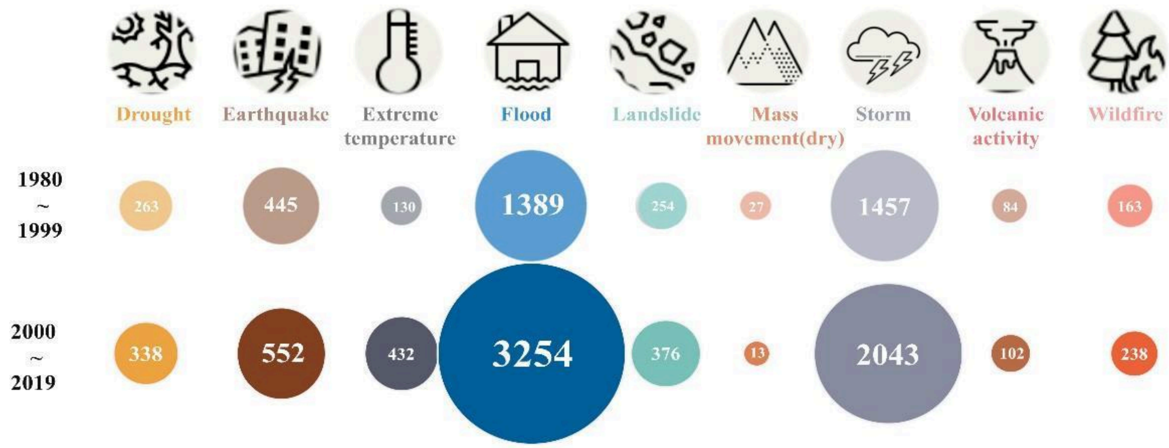

Figure 1. The classifications of disaster incidents from for the years 1980–1999 and 2000–2019(Cho et al. 2022)

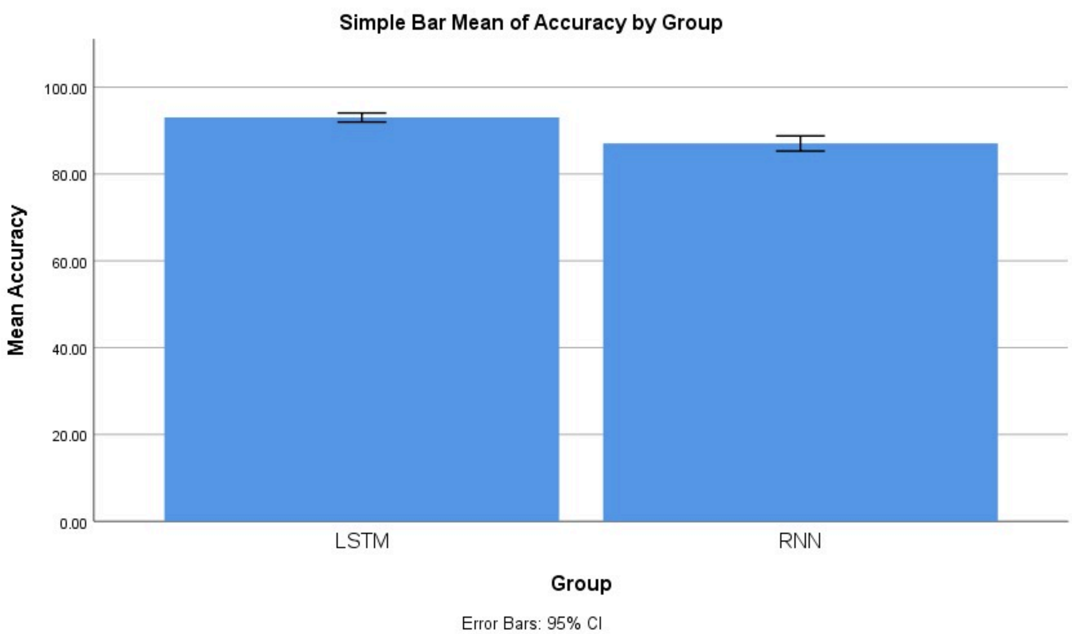

Figure 2. Mean accuracy comparison between RNN and LSTM algorithm. Compared to the RNN algorithm's mean accuracy of 87.0345, the LSTM's mean accuracy of 93.0095 is superior. Long Short-Term Memory (LSTM) vs Recurrent Neural Network (RBFNN) on the X-axis. Y-axis: Accuracy mean