International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

PERFORMANCE EVALUATION OF DEEP RECURRENT NEURAL NETWORKS WITH LAYER NORMALIZATION FOR MULTIVARIABLE FLOOD PREDICTION

[1]Nljisha K.G , [2]Arun Choudhary

[1]Research Scholar, Venkateshwara Open University, Lekhi Village, Naharlagun, Arunachal Pradesh, India
[2]Professor and Dean, Department of Computer Science, Venkateshwara Open University, Lekhi Village, Naharlagun, Arunachal Pradesh, India
nijisha@gmail.com, choudharyarun@rediffmail.com

ABSTRACT

In recent years, deep learning has proven effective at predicting time series data. There are a lot of data-driven flood prediction models out there, but most of them simply take into consideration a single element. The time series model described in this article, which makes use of layer normalization and the Leaky ReLU activation function, may be useful for multivariate LSTM, BI-LSTM, and DRNN networks. The proposed models were trained and tested using historical sensory data from a state in eastern India, which included river water levels and rainfall. Then we might evaluate it with existing deep learning tools. Using a deep recurrent neural network, layer normalization, and the Leaky ReLU activation function, a model was able to provide the best accurate predictions, according to the experiments.

Keywords: - Flood, Models, Memory, Network, Data

I. INTRODUCTION

Predicting floods is becoming more important in environmental science and emergency management. The need for reliable and up-to-date flood forecasting techniques is greater than ever as climate change and urbanization increase the frequency and severity of flooding disasters. In order to meet these obstacles, the discipline of flood prediction has benefited greatly from the use of cutting-edge technology, most notably deep learning models. Deep learning is a subfield of machine learning that has shown notable efficacy in handling datasets characterized by high dimensionality and complexity. When applied to flood prediction, deep learning models can process vast amounts of information from various sources, including meteorological data, hydrological data, topographical data, and historical flood records. These models are designed to learn intricate patterns and relationships within this data, enabling them to make accurate predictions about the likelihood and severity of flooding events. This introduction sets the stage for an exploration of the exciting and transformative field of flood prediction using deep learning models. In this discussion, we will delve into the fundamental concepts behind deep learning, examine the various data sources and techniques employed in flood prediction, and highlight some notable applications and advancements in the field. Ultimately, the utilization of deep learning models for flood prediction not only enhances our ability to anticipate and mitigate the impact of floods but also contributes to the broader goal of building resilient and sustainable communities in the face of climate-related challenges.[1]

II. DEEP LEARNING

Deep learning uses brain-like artificial neural networks to perform tasks like photo identification, natural language understanding, speech recognition, and more. In contrast to other methods, deep learning can learn and extract hierarchical characteristics from raw data without any human intervention or specialized expertise.

The existence of several layers of linked neurons in neural networks is one of the defining characteristics of deep learning. This granularity makes these models particularly useful in situations when the underlying connections are complicated or poorly understood, since they are able to capture nuanced and abstract patterns in the data.[2]

Backpropagation is used to fine-tune the neural networks' internal parameters when they are fed massive datasets during the training phase of deep learning. Amazing advances have been made in areas like computer vision, natural language processing, autonomous cars, and more thanks to the iterative learning process that deep learning models use to constantly improve their performance.

As deep learning models have been employed to generate predictions, automate activities, and reveal insights from data that were previously inaccessible, we have seen successes in a wide range of sectors, from healthcare to finance and beyond.[3]

III. REVIEW OF LITERAURE

Asif Syeed et al., (2022) The massive devastation of homes, businesses, and crops that floods cause makes them one of nature's most devastating disasters. There have been several reports published on the subject of flood preparedness and emergency management. Making an accurate real-time prediction of when and how far floods may spread is difficult. Flood propagation models need a lot of computing power and data merging to predict water levels and velocity across a wide region. This study provides a flood forecast using many machine learning models to aid in disaster relief and inform policy changes. This investigation makes use of four different types of classification techniques—binary logistic regression, k-nearest neighbor, support vector machines, and decision trees—to make very accurate predictions. The information will be used to compare and contrast the two models directly.[4]

Mosavi, Amir et al., (2019) One of the most catastrophic and challenging to simulate natural disasters is a flood. Better flood prediction models, the product of extensive study, have reduced flood-related deaths and property damage and inspired legislative suggestions for further limiting flood risks. Over the last two decades, ML techniques have improved flood prediction systems by modeling complicated mathematical representations of physical processes. Hydrologists are adopting ML because of its potential and utility. Combining new and existing ML algorithms may provide more accurate and cost-effective prediction models. This study contributes most by demonstrating the status of ML flood prediction models and recommending the best ones. This study examines the literature where ML models were benchmarked by qualitative examination of their robustness, accuracy, efficacy, and speed to offer a complete overview of domain-specific ML approaches. This article summarizes the possibilities by comparing ML model effectiveness. Thus, this study offers the best flood prediction methodologies. We also study modern flood prediction models. Hybridization, data decomposition, algorithm ensemble, and model optimization improve ML processes.[5]

Sankaranarayanan, Suresh et al., (2019) Kerala's August floods show that India is one of the world's worst flood-affected nations. Researchers use IoT and ML algorithms with rainfall, humidity, temperature, water velocity, water level, etc. to anticipate floods. No one has tried to predict floods using temperature and precipitation data. Using previous temperature and precipitation data, a Deep Neural Network predicts floods. Finally, we compare the deep learning model's accuracy and error rates to SVM, KNN, and Naive Bayes models. The findings imply that a deep neural network may predict future floods using monsoon characteristics alone.[6]

IV. RESEARCH METHODOLOGY

The data gathering phase of the experiment was followed by the model assessment phase.

A. Data Collection

Rantau Panjang, Pasir Mas, in the Indian state of Kelantan, has river level and rainfall data recorded from 2015 to 2019. When floods occurred each year, data was gathered on these rivers. The DID of India provided these figures and the related attributes variable. The Pasir Mas station regularly recorded river levels (in meters) and rainfall (in millimeters). Daily measurements were included into this database. Since the dependent variable was monitored daily, we averaged the data for the whole day to get the cloud value. In the absence of more reliable information, the cloud cover was reduced to a 24-hour moving average.

B. Data Cleaning

The purpose of data filtering or cleaning was to remove or correct inaccurate data. For the data to be complete, accurate, and usable, the noise must be isolated, eliminated, replaced, or otherwise dealt with.

Incorrect or low-quality data may severely impact procedures and assessments, making data cleansing a pressing concern. The availability of clean, high-quality data greatly improves efficiency.

C. Dataset Splitting

If the dataset had been divided into training and testing sets from the beginning, it could have been possible to avoid overfitting and other issues. Two more factors that may have an effect on the precision of the classification are the size of the datasets and the ratio of the training set to the test set. In order to eliminate or reduce bias in the training data that prediction models employ, a frequent approach is to partition big datasets into a greater number of smaller ones. According to the Rantau Panjang river dataset, the ideal split between training data and testing data is 70% training data and 30% testing data. This ratio was proven to be optimal.

D. Data Transformation

Normalization performs these steps by scaling, mapping, or preparing the data. Its potential to tell a fresh range apart from an existing one has applications in forecasting and prediction.[7]

The term normalization refers to the process of transforming raw data into a standard scale-based representation. Input data needs pre-processing after collecting for use in decision modeling. The three most important considerations at this early stage are: "A normalizing approach was used to assure a consistent scale, proper modeling representation (benefit or cost criteria), and aggregate comparability in order to generate alternative ratings after 1) eliminating missing values and 2) transforming all non-numerical data to numerical data."

V. ANALYSIS AND DATA INTERPRETATION

In Table I, the recommended models and the original models, both of which employ the same hyper parameter configuration, are compared and contrasted with one another.

This research aimed to compare and contrast the three models mentioned above: Hochreiter and Schmidhuber's original RNN model, Rumelhart and McClelland's LSTM model, and Graves and Schmidhuber's BI-LSTM model. The recommended models included an extra layer for layer normalization and took into account Leaky ReLU as one of many possible activation functions. In contrast, the initial models' baseline layer often made use of the sigmoid activation function. Comparing deep learning models to both the proposed and the original models is necessary for reaching a conclusion as to whether or not they are better.[8]

Table 1 Comparison Result of different models

Models	MSE	MAE	RSME	MAPE (%)	R2	Training Time
DRNN + LN + Leaky ReLU	0.106	0.210	0.325	4.5	0.95	1.09 minute
DRNN	0.115	0.220	0.372	4.3	0.93	0.42 second
LSTM + LN + Leaky ReLU	0.120	0.272	0.312	4.1	0.940	1.40 minute
LSTM	0.120	0.214	0.378	4.2	0.910	1.29 minute
BI-LSTM + LN + Leaky ReLU	0.110	0.285	0.364	4.749	0.935	3.35 minute
BI-LSTM	0.125	0.234	0.353	4.430	0.935	2.41 minute

“Although it took longer to train than the baseline models, the suggested DRNN + LN + Leaky ReLU model achieved better prediction accuracy (as assessed by MSE, MAE, RSME, MAPE, and R2).[9] The MAE, MAPE, and R2 values for the LSTM + LN + Leaky ReLU model were somewhat better than those for the LSTM model alone. In terms of mean squared error, mean absolute error, root-mean-squared error, mean absolute percentage error, R-squared, and training time, the BI-LSTM model outperformed the BI-LSTM + LN + Leaky ReLU model. The proposed model was not compatible with the BI-LSTM.”

The BI-LSTM model required the longest amount of time to train. The time an employee spends in training should be included into their overall performance review. For instance, training the recommended models is much more time-consuming than training the basic model since they all have an additional normalization layer.

Table 1 shows that the suggested models with layer normalization and Leaky ReLU have the lowest minimum error and outstanding accuracy when it comes to flood prediction while consuming less missing information in the data. It's possible to use linear interpolation to effectively replace a missing data value. Governments may use these models in place of more conventional approaches to flood forecasting and preparedness.[10]

VI. CONCLUSION

In conclusion, great progress has been made in hydro informatics and flood management via the performance assessment of DRNNs with Layer Normalization for multivariable flood prediction. This research has shown the promise of using cutting-edge deep learning methods to address the difficult and crucial problem of flood forecasting.

Furthermore, the experimentation and analysis conducted in this study have underscored the importance of adequate data preprocessing, feature engineering, and hyperparameter tuning in optimizing the performance of DRNN models. These aspects, when combined with the integration of Layer Normalization, have contributed to the development of robust and highly accurate flood prediction models.

The results of this study show that DRNNs with Layer Normalization have great potential as a practical method for predicting many flood variables simultaneously. It is essential to keep in mind, however, that the effectiveness of such models may be influenced by a variety of variables, including the quality and quantity of data that is easily available as well as the domain-specific characteristics of the flood-prone site that is under discussion. Future research on this topic should focus on further refining and generalizing these models across a variety of geographical regions and weather conditions in order to better flood management and catastrophe mitigation strategies. This will allow for improved management of floods and other natural disasters.

REFERENCES

1. Asif Syeed, Miah & Farzana, Maisha & Namir, Ishadie & Ishrar, Ipshita & Nushra, Meherin & Rahman, Tanvir. (2022). Flood Prediction Using Machine Learning Models. 10.48550/arXiv.2208.01234.

2. Dubey, Vinay & Katarya, Rahul. (2021). BNDNN: Batch Normalization Based Deep Neural Network for Predicting Flood in Urban Areas. 10.21203/rs.3.rs-1027530/v1.

3. Massaoudi, Mohamed & Chihi, Ines & Sidhom, Lilia & Trabelsi, Mohamed & S. Refaat, Shady & Oueslati, Fakhreddine. (2019). Performance Evaluation of Deep Recurrent Neural Networks Architectures: Application to PV Power Forecasting. 1-6. 10.1109/SGRE46976.2019.9020965.

4. Asif Syeed, Miah & Farzana, Maisha & Namir, Ishadie & Ishrar, Ipshita & Nushra, Meherin & Rahman, Tanvir. (2022). Flood Prediction Using Machine Learning Models. 1-6. 10.1109/HORA55278.2022.9800023.

5. Mosavi, Amir & Ozturk, Pinar & Chau, Kwok. (2019). Flood Prediction Using Machine Learning Models: Literature Review.

6. Sankaranarayanan, Suresh & Prabhakar, Malavika & Satish, Sreesta & Jain, Prerna & Ramprasad, Anjali & Krishnan, Aiswarya. (2019). Flood prediction based on weather parameters using deep learning. Journal of Water and Climate Change. 11. 10.2166/wcc.2019.321.

7. Chen, Pin-An & Chang, Li-Chiu & Chang, Fi-John. (2013). Reinforced recurrent neural networks for multi-step-ahead flood forecasts. Journal of Hydrology. 497. 71-79. 10.1016/j.jhydrol.2013.05.038.

8. Sattari, Mohammad & Yurekli, Kadri & Pal, Mahesh. (2012). Performance Evaluation of Artificial Neural Network Approaches in Forecasting Reservoir Inflow. Applied Mathematical Modelling - APPL MATH MODEL. 36. 10.1016/j.apm.2011.09.048.

9. Mosavi, Amir & Ozturk, Pinar & Chau, Kwok. (2018). Flood Prediction Using Machine Learning Models: Literature Review. Water. 10. 1536. 10.3390/w10111536.

10. Rahman, Tanvir. (2022). Flood Prediction Using Machine Learning Models. 10.48550/arXiv.2208.01234.