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Short communication

Daily rainfall prediction using long short-term memory (LSTM) algorithm

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Rainfall is a highly variable meteorological parameter that significantly impacts various hydrological and agricultural systems. Changing environments and topography can further exacerbate these issues, underscoring the urgent need for accurate daily rainfall predictions in specific regions (Chen *et al.,* 2022). In areas reliant on monsoon rains, the timing and quantity of rainfall greatly influence crop yields, impacting food security and farmers' livelihoods. Rainfall prediction has been one of the important field of research in ancient science (Vaidya *et al.,* 2023) Accurate daily rainfall predictions are essential for regions dependent on agriculture, water management, and disaster preparedness.

Advancements in artificial intelligence (AI) have revolutionized weather forecasting, particularly through machine learning and deep learning techniques. AI systems can analyze vast amounts of data to forecast weather patterns with unprecedented detail and accuracy. Previous research has proposed various methods for predicting rainfall using AI and statistical analysis (Barrera-Animas *et al.,* 2022; Chen *et al.,* 2022; Gill *et al.,* 2023; Ray *et al.,* 2023). Among these methods, long short-term memory (LSTM) networks are particularly effective in modeling temporal correlations in meteorological data, enabling more accurate forecasting of complex phenomena such as rainfall, temperature fluctuations, and storm patterns. The ability of LSTM to capture long-range dependencies makes it invaluable for weather forecasting, assisting meteorologists in providing timely and reliable information essential for agricultural planning, disaster preparedness, and other weather-sensitive industries (Endalie *et al.,* 2022; Gauch *et al*., 2021). Therefore, an investigation was carried out for daily rainfall prediction using the LSTM algorithm; by applying various recurrent neural network (RNN)-based deep learning architectures, we aim to enhance rainfall predictions driven by time series data.

Dataset

The weather data from AWS Almora station (29.6002° N, 79.6651° E, 1620.0 meters) located in Almora district of Uttarakhand from January 2020 to September 2023 was obtained from the India Meteorological Department (IMD). The input features consist of temperature, relative humidity, wind direction, wind speed, sea level pressure, and mean sea level pressure and the daily rainfall (mm). The dataset includes various attributes, a total of 32,868 rows, and approximately 13% of the data points have missing values. Automatic Weather Station data often encounter missing values, outliers, and anomalies due to sensor faults, calibration issues, sensor offset changes, communication failures, and power issues. Various preprocessing techniques, such as nearest station data imputation and spline interpolation, are applied to enhance the quality of this data. The pre-processed data is divided into training, testing, and validation sets. It is then fed into the model, tested, evaluated, and deployed for real-time extreme rainfall prediction. (Poornima *et al.,* 2019).

Long short-term memory (LSTM) algorithm

LSTM is highly effective for time series data prediction because it captures long-term dependencies and patterns. Its architecture is designed to retain information over extended sequences, making it well-suited for handling sequential data. With advanced configuration options, LSTM models can be tailored to optimize performance, allowing for more accurate forecasts. This makes LSTM particularly useful in complex time series applications, such as stock price prediction, weather forecasting, or any scenario where past data significantly influences future outcomes. The information flows through an LSTM unit, enabling it to effectively acquire and retain information across extended periods for a

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Table 1: LSTM models configuration summary

Model	Layers	Activations	Optimizers	Epochs	Learning rate	Batch size
Model-1	5	ReLU	Adam	100	0.000001	32
Model-2	1	ReLU	Adam	100	0.001	72
Model-3	1	ReLU	Adam	300	0.1	72
Model-4	2	ReLU	Adam	100	0.000001	72
Model-5	3	ReLU	Adam	100	0.000001	72
Model-6	3	ReLU	Adam	300	0.5	200
Model-7	1	ReLU	Adam	100	0.000001	32

Table 2: Model performance evaluation using metrics.

Model	RMSE	MSE	MAE	R^2
Model-1	0.029	0.0009	0.004	0.278
Model-2	0.018	0.0003	0.004	0.730
Model-3	0.017	0.0003	0.006	0.764
Model-4	0.018	0.0003	0.005	0.725
Model-5	0.012	0.0002	0.005	0.871
Model-6	0.030	0.0009	0.005	0.228
Model-7	0.009	0.0001	0.004	0.930

variety of applications, including time series prediction and natural language processing (Endalie *et al.,* 2022; Sherstinsky *et al.,* 2020; Frame *et al.,* 2022). To limit gradient vanishes by multiplying the sequence of input to layers of LSTM, down the prediction error, and generate correct rainfall prediction using Optimizer as Adam, the LSTM algorithm of various configurations is experimented with in this research. Seven models were developed to experiment with different combinations of layers, learning rates, and epochs (Table 1). This variation allows us to test the impact of model complexity and learning speed on performance. We aim to identify the best configuration for optimal results across different training conditions by adjusting parameters like batch size and optimizers.

The model was trained with the “keras” Python library on a Tensorflow backend. Hunting for hyperparameters was a crucial step before learning. Every hyperparameter, such as dropout rate, hidden node numbers in each layer, learning rate, hidden layers, and so forth, has a set of values allocated to it. After that, the machine was free to select a value at random for each hyperparameter from the set. After examining numerous models with different combinations of hyperparameter values, we can usually determine which model was “best” and match “best” hyperparameters.

The data from 2020 to 2023 were utilized in the prediction. A training dataset and a testing dataset were separated within this dataset. The suggested LSTM-based RNN model was specifically trained using rainfall data over the four years from 2020 to 2023. The dataset from 2023 was used for the testing model. Pressure, temperature, humidity, wind direction, and speed were considered as input variables to predict the variable rainfall. To aid with learning and prediction, all the experimental variables were given to the network during the training phase, along with the outcome variable rainfall corresponding to each one. Seven combinations of parameters, such as activation functions, layers, epochs, etc., were used to evaluate the LSTM method. Metrics like RMSE, MSE, MAE, and R^2 were used for evaluation of model performance.

After testing various configurations of LSTM, Model-7 was found to perform best as it exhibited the lowest RMSE and highest R^2 value (Table 2). This has performed well due to its simpler architecture with one layer, which is less prone to overfitting. A very low learning rate allows the model to make fine adjustments during optimization, leading to more stable convergence and avoiding large updates that could cause instability during training. LSTM model 7 was recommended to forecast daily rainfall with 93% accuracy. This model fits well with real-time data, showing minimal errors.

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Data availability: Required data is available at the National Data Centre (NDC), India Meteorological Department, Shivajinagar, Pune.

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REFERENCES

Barrera-Animas, A.Y., Oyedele, L.O., Bilal, M., Akinosho, T.D., Delgado, J.M.D. and Akanbi, L.A. (2022). Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting. *Mach. Learn. Appl.,* 7:100204.

Chen, C., Zhang, Q., Kashani, M.H., Jun, C., Bateni, S.M., Band, S.S., Dash, S.S. and Chau, K.W. (2022). Forecast of rainfall distribution based on fixed sliding window long short-term memory. *Eng. Appl. Comput. Fluid Mech.,* 16(1):248-261.

Endalie, D., Haile, G. and Taye, W. (2022). Deep learning model for daily rainfall prediction: Case study of Jimma, Ethiopia. *Water Supply*, 22(3):3448-3461.

Frame, J.M., Kratzert, F., Klotz, D., Gauch, M., Shalev, G., Gilon, O., Qualls, L.M., Gupta, H.V. and Nearing, G.S., (2022). Deep learning rainfall–runoff predictions of extreme events. *Hydrol. Earth Syst. Sci.,* 26(13):3377-3392.

Gauch, M., Kratzert, F., Klotz, D., Nearing, G., Lin, J. and Hochreiter, S. (2021). Rainfall-runoff prediction at multiple timescales with a single Long Short-Term Memory network. *Hydrol. Earth Syst. Sci.,* 25(4):2045-2062.

Gill, K. K., Bhatt, K., Kaur, B. and Sandhu, S. S. (2023). ARIMA approach for temperature and rainfall time series prediction in Punjab. *J. Agrometeorol., 25*(4): 571-576. https://doi.org/10.54386/jam.v25i4.2250

Poornima, S. and M. Pushpalatha. (2019). Prediction of rainfall using intensified LSTM based recurrent neural network with weighted linear units. *Atmosphere* 10.11 (2019): 668.

Ray, Mrinmoy, K. N. Singh, Soumen Pal, Amit Saha, Kanchan Sinha and Rajeev Ranjan Kumar (2023). Rainfall prediction using time-delay wavelet neural network (TDWNN) model for assessing agrometeorological risk. *J. Agrometeorol., 25*(1): 151-157. https://doi.org/10.54386/jam.v25i1.1895

Sherstinsky, A. (2020). Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Physica D.,* 404, 132306

Vaidya, V. B., Pandey, V. and Dhabale, S. (2023). Ancient science of weather forecasting in India with special reference to rainfall prediction. *J. Agrometeorol., 25*(4): 477-490. https://doi.org/10.54386/jam.v25i4.2422