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UTILIZING DEEP LEARNING MODELS IN KABIRDHAM, CHHATTISGARH, TO FORECAST AND MODEL RAINFALL

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ABSTRACT

Deep learning has emerged as a key area for modeling and forecasting complex time series data. The future performance of Kabirdham rainfall data was investigated in this machine learning project. To construct and validate the model, the dataset is divided into 35% test sets and 65% training sets. We utilized the Root Mean Square Error (RMSE) measure to compare these deep learning models. In this data set, the Modified BPN ANN model performs better than the BILSTM and GRU models. The predictions of these three models are comparable. The development of a comprehensive Kabirdham weather forecast book might benefit from this knowledge. Scholars and policymakers would both benefit from this information. Beyond statistical methods, we think this study can be utilized to apply machine learning to complicated time series data.

Keywords: Rainfall, Deep Learning, ANN, Kabirdham

1. INTRODUCTION

In terms of population density, the Kabirdham Chhattisgarh region is the second most densely populated federal territory in the country. With more than 8,22,526 residents, Kabirdham is the medium monocentric agglomeration in Chhattisgarh, India [1,2]. There is no administrative center because government officials are dispersed across Kabirdham and the rest of the oblast. 8,22,526 persons were tallied in the 2010 census, while 7,231,068 were counted in the 2011 census. The city is situated in the Kabirdham region, with coordinates of 22°01' N latitude and 81°13' E longitude. There is a high level of regional industrialization [3]. Kabirdham experiences long, warm summers and brief, chilly winters due to its humid continental climate. Between 42°C and 15°C is the average temperature. The months of January and February are the coldest. Average high temperature: 42°C; average low temperature: 15°C.

This study predicts precipitation patterns using IMPD data from 1901 to 2019 and a deep learning Modified BPN ANN model. According to the present study, precipitation in Kabirdham rose. Predicting time series data requires knowledge of the sequence being modeled and may involve cross-dimensional spatial dependencies. Historically, both conceptual and physical models have been employed to predict rainfall [4]. While conceptual models are better suited for daily time-scale phenomena, physical models are capable of making forecasts and predictions almost every day. Precipitation and runoff cannot be reliably predicted by conceptual and physical models that employ temporal scales, particularly when spatial resolution is limited [5,6]. Furthermore, these models' ability to accurately predict sequence data with ambiguous or constrained quasi-periodic dynamics is restricted by the physical characteristics they require [7–10].

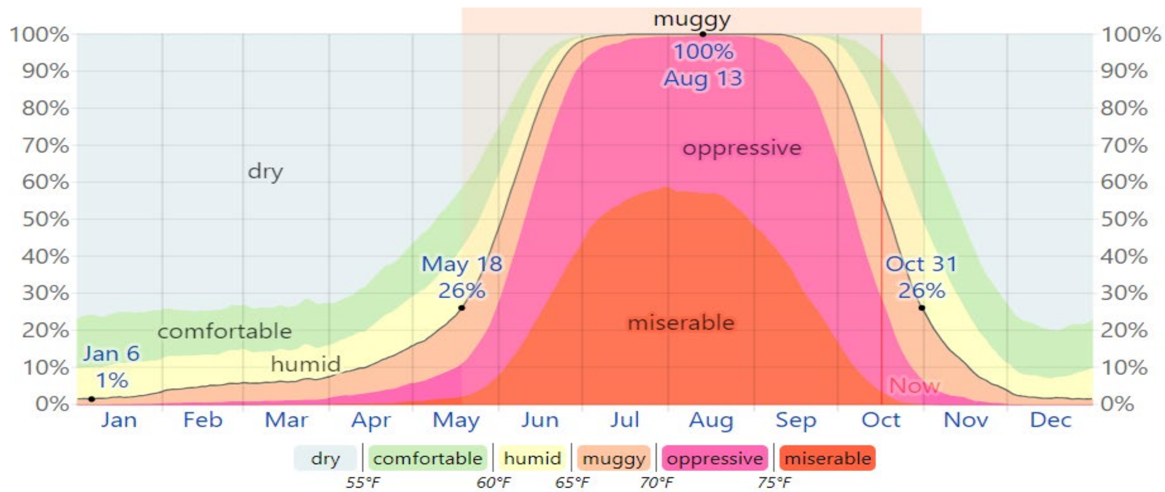

Fig.1: The proportion of time spent in each humidity comfort level, broken down by dew point

Source:https://weatherspark.com/y/110376/Average-Weather-in-Kawardha-Chhattisgarh-India-Year-Round#Sections-Humidity

The closest statistical approach to deep learning, Modified BPN ANN mode, was utilized to predict rainfall. Statistical techniques are only reliable for time series data with irregular trends both within and between seasons, claim Poornima and Pushpalatha [11]. Precipitation forecasts could be enhanced by a data analysis technique. This skill is caused by the capacity to estimate the dynamics and patterns of string data without the need of parameters. It also takes system noise and observation randomness into consideration. When analyzing precipitation time-series trends, deep learning is recommended (Kratzert 2018). [12] pointed out that [13] recommended using the Modified BPN ANN mode for rainfall forecasting due to its better long-term analysis results. Other precipitation forecasting experiments, like the one in [14], make use of the RBF network and empirical decomposition models. The samples demonstrated that seasonal degradation and cyclical oscillations in rainfall and runoff time sequence data were not taken into account by the techniques. [15] created a training program for artificial neural networks (ANNs) that enhances Kentucky River watershed flow-volume estimates by utilizing genetic algorithms. [16] investigated the little Malaprabha River Basin in India. They employed a modular neural network to accurately simulate the intensity of rainfall and runoff. Results from [17] were superior to those from [18]. The Modified BPN ANN mode approach dynamically integrates prior learning experiences through internal repetition. [19] discovered that feed-forward neural networks without internal states are less computationally reliable and less coherently designed than the Modified BPN ANN mode. By showcasing the essential characteristics of time series data, the modified BPN ANN mode may faithfully reproduce and mimic chaotic series. Long time delays and both low- and high-frequency time-series signals work well with the modified BPN ANN mode. ANN and statistical models like ARMA and ARIMA are not as good at learning and capturing time-series data as the modified BPN ANN mode. For evaluating various timeseries data, this makes the Modified BPN ANN mode advantageous [20,21].

In Kabirdham, where there are insufficient hydrological and meteorological monitoring networks, precipitation trends are analyzed and predicted using a modified BPN ANN model. to comprehend the relevance of a model in this context. The benefits of the Modified BPN ANN Model in precipitation applications have not been compared in the literature because of a lack of meteorological data. In this study, rainfall patterns in Kabirdham are analyzed and predicted using meteorological data from IMPD.

2. MATERIALS AND PROCEDURES

The output from the previous stage serves as the input for the subsequent phase of a Recurrent Neural Network (RNN). Typically, inputs and outputs in traditional neural networks are independent. Nonetheless, earlier words must be kept since they are essential for anticipating the following word in a sentence. As a result, the RNN was developed with a Hidden Layer to address this issue. The Hidden state of RNNs, which houses sequence data, is their most well-known feature. The "memory" of recurrent neural networks (RNNs) is where earlier computations are stored. Since it generates the output by applying the same operation to all inputs or hidden layers, it employs comparable parameters for each input. In contrast to other neural networks, this simplifies the parameters. Modified BPN ANN Model: Sequence prediction order dependency can be learned by recurrent neural networks such as Modified BPN ANN Model. Significant effect has been made by the Modified BPN ANN Model network, which can learn from sequential data. Modified BPN ANN Models are more accurate than RNNs because they can capture long-range dependencies. Back-propagation complicates the backward flow of errors in the RNN design. The back-propagation method combines functions using the chain rule. It works well to use Stochastic Gradient Descent (SGD) to find the local loss function minimum. We can determine the gradients of nodes with a starting point by determining its gradient and proceeding in the opposite direction after obtaining the gradients from the computational network nodes. This approach is the most effective for locating a local minimum. Memory cells from the modified BPN ANN Model receive and store unit outputs over a number of time steps. Cell states are used by the Modified BPN ANN Model memory cell to store data over time. To control the flow of information between time intervals, it also features input, output, and forgetting gates.

This study used neural networks based on the Modified BPN ANN Model and time-series rainfall data to forecast background radiation. When attempting to explain the persistent dependence of recurrent neural network arrangements, the vanishing gradient problem comes up. Gradients for the first few input points vanish and become zero as the input sequence lengthens, making the initial stages less significant. The output of the Modified BPN ANN Model is equal to its input because its activation function is the identity function. Due to the recurrent nature of the Modified BPN ANN Model, the derivative of this function is always 1.0. Backpropagated gradients stay constant as a result. The activation functions of the nodes determine their output. Sigmoid and hyperbolic tangent activation functions are used in modified BPN ANN Model networks.

The current architecture of the Modified BPN ANN Model employs the tanh function for the candidate vector that updates the cell state vector and the sigmoid function for the input and forget gates. BPN ANN Model Model Modification: The advantages of the BiRNN and Modified BPN ANN Model models are combined in the hybrid Modified BPN ANN Model model. The BiLSTM model is used to transmit and receive data. A bidirectional neural network called BiLSTM records both past and future data. BiLSTM is one of several models for parallel processing. The wp and wq queries are initially encoded using two Modified BPN ANN Model models. Model GRU: GRUs enhance conventional recurrent neural networks. GRU addresses the traditional RNN vanishing gradient problem by using update and reset gates. These two vectors decide the output information. Their ability to be trained to preserve historical data without cleaning it up or eliminating unnecessary information from the forecast makes them special.

3. RESULT DISCUSSED

Table 1 showed that the average rainfall increased from 1.30 mm to 159.40 mm from January 1973 and December 2024. A mesokurtic distribution, which has heavier tails than a normal distribution (more in the tails), is indicated by a humidity value of 3.52. A wind value of (0.87), which is greater than 0.5, comes next, indicating that the distribution is roughly non-symmetric. The data set's IMPD is displayed via these descriptive statistics. We must use neural network approaches for this primary reason. Table 1. Characteristic

Table 1: presents descriptive data regarding Moscow's average monthly rainfall between January 1973 and December 2024.

	Minimum	Maximum	Humidity	Wind Speed	Standard Deviation
Kabirdham	1.40	169.50	3.65279	0.772595	28.25185

Table 2 provided us with information regarding the training data's correctness, which is 65% of the Kabirdham monthly average rainfall data set. Mean Error (ME), Room Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Percent Error (MPE), and Auto Correlation Function (ACF) are among the statistics provided for measuring accuracy.

Table 2: Training data accuracy 66% of the Kabirdham monthly average rainfall data set

Model	ME	RMSE	MAE	MPE	MAPE	ACFI
Modified BPN ANN Model	1.204391	24.257989	19.721891	25.695463	48.536861	1.1684
BI-LSTM	1.705856	25.648263	20.363736	25.42.5147	50.811023	1.41936
GRU	1.893711	25.922630	20.463049	24.126313	49.570031	1.93367

Table 3 makes it evident that the Modified BPN ANN model did well with the provided data set. Data analysis revealed that modified BPN ANN model networks were more predictive. The Modified BPN ANN model's ME, RMSE, MAPE, MAE, and MPE values are 0.104, 23.25, 47.35, 18.61, and -24.96, respectively. The Modified BPN ANN model has a lower value for all of the mistakes for the training data set. All of the values for GRU and BiLTSM are greater than those for the Modified BPN ANN model. It demonstrates the LTSM model's effectiveness. The Modified BPN ANN model's ACF value is -0.011, BiLTSM's is 0.041, and GRU's is 0.069. ACF's negative value indicates a breach of independence. Table 3 shows the test data's accuracy, or 35% of the whole data set. We utilized RMSE for this, and we found that the Modified BPN ANN model's RMSE value is 26.29, BiLTSM's is 27.70, and GRU's is 27.67.

Table 3: Testing data accuracy 35% of Kabirdham's monthly average rainfall data set

Model	RMSE
Modified BPN ANN Model	27.929891
BI-LSTM	28.070347
GRU	28.747467

Table 4 leads us to the conclusion that the Modified BPN ANN Model works flawlessly with both trained and test data. Because the Modified BPN ANN Model's accuracy metrics (ME, RMSE, MAE, MPE, MAPE, and ACF1) have lower values than those of the BiLTSM and GRU models, the model's accuracy is extremely high. Therefore, we perform better than the Modified BPN ANN Model in predicting rainfall in Kabirdham.

Table 4: Predicting Kabirdham's monthly average rainfall

Month	2022	2023	2024
January	45.973110	49.437953	50.100678
February	46.687705	48.181847	49.483561
March	47.946085	48.739083	50.027001
April	49.821248	49.776533	50.183505
May	49.343065	52.329471	51.517409
June	52.739379	52.007831	51.296803
July	55.633395	53.095318	51.579430
August	55.594684	52.786532	51.928573
September	53.679227	52.645381	51.097260
October	52.353882	51.800452	51.116342
November	50.643289	50.567328	51.196436
December	48.785291	50.996173	50.973461

Table 4 shows the Modified BPN ANN model's prediction of monthly average rainfall. Table 4 provides the best predicted values for the current study since the Modified BPN ANN model is the best of the several RNN models. 36 consecutive months, from January 2022 to December 2024, are forecasted. The trend of the forecast data and the predictions of the training and testing data using the three models—the Modified BPN ANN model, the BiLTSM model, and the GRU model—are shown in Figures 1-3.

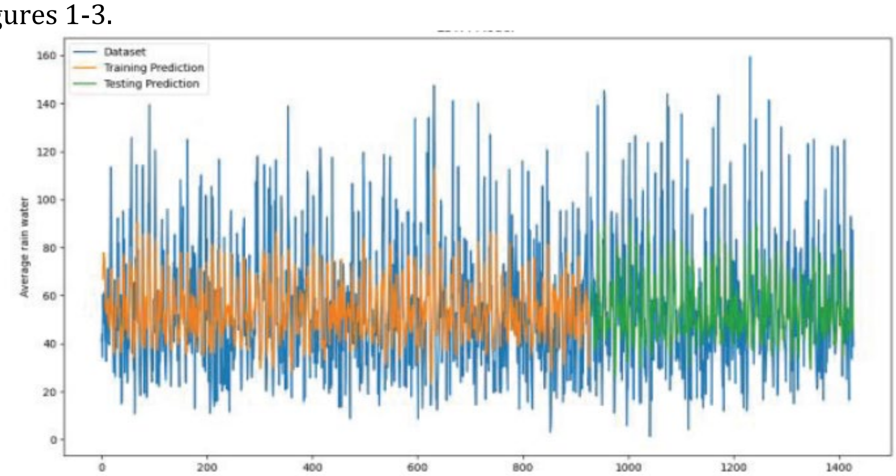

Fig 2: Modified BPN ANN Model

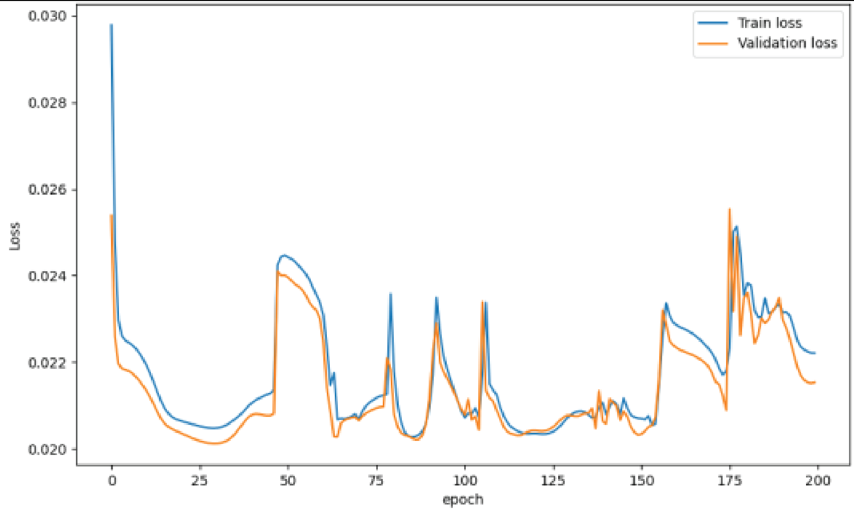

Fig 3: Model Train vs Validation loss for Modified BPN ANN Model

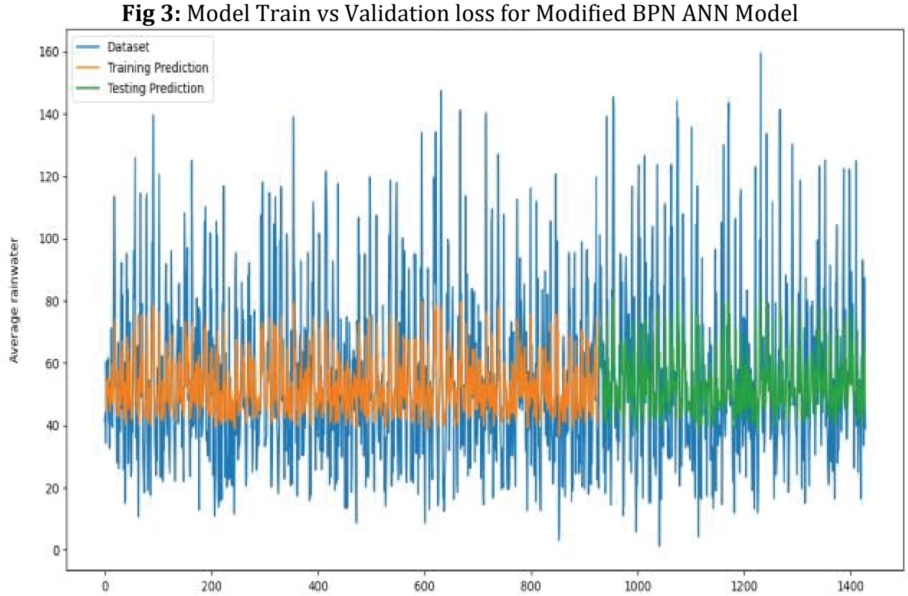

Fig. 4: BiLTSM Model

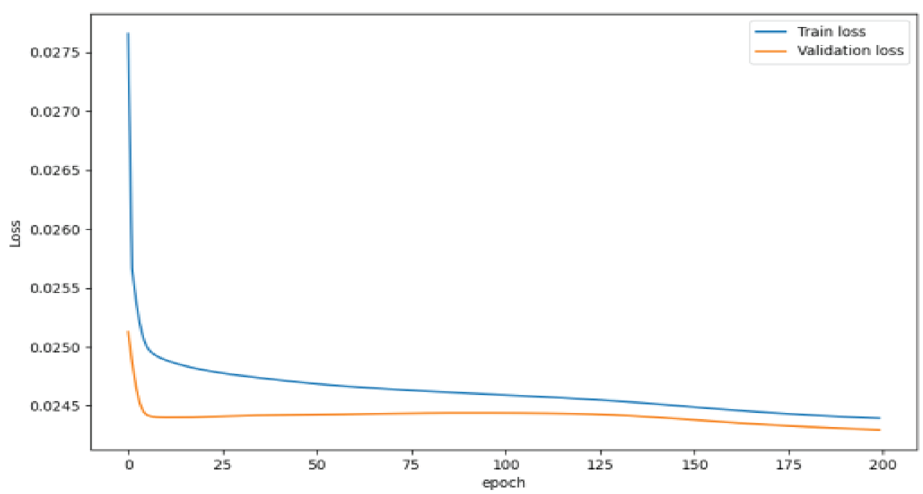

Fig. 5: Model Train vs Validation Loss for BiLSTM

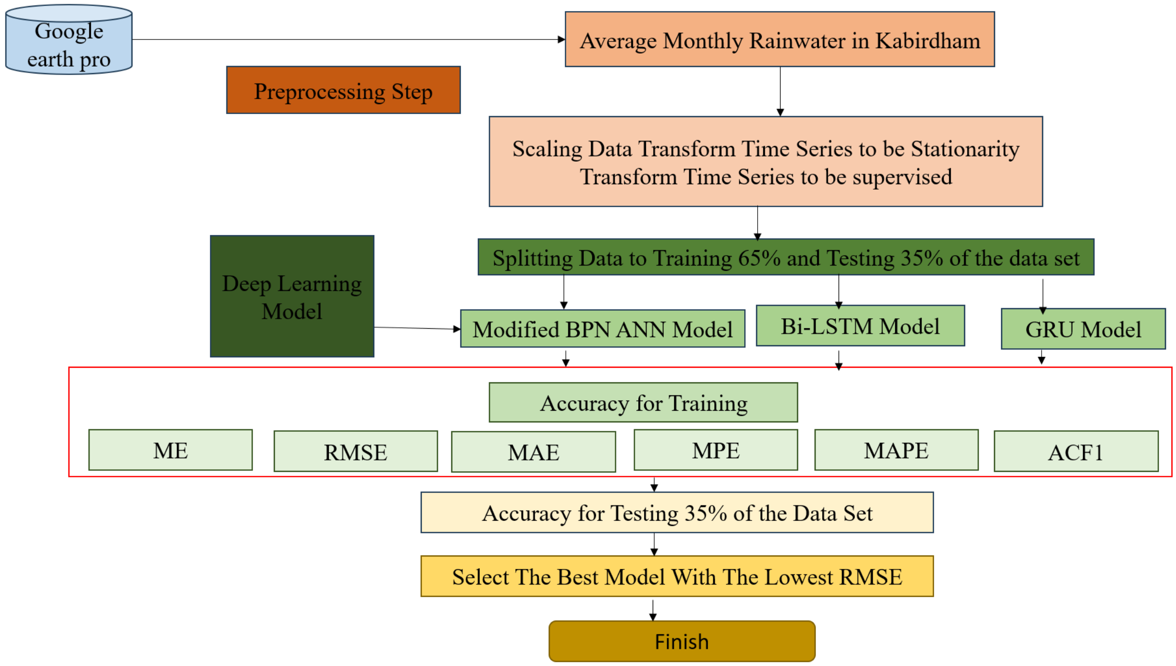

Fig. 6: Algorithm includes the full technique for all models utilized, including GRU, BiLTSM, and the Modified BPN ANN Model

In this study, we demonstrate how machine learning techniques can be applied to Moscow's rainfall data to forecast future behavior. The deep RNN technique yielded an excellent outcome. In order to forecast rainfall in Moscow, three deep learning techniques—LSTM, BiLSTM, and GRU models—are employed. The goal is to determine which model performs best based on varying goodness of fit in both the training and testing data sets. Compared to the other two models, the LSTM model provided a better approach. The LSTM model showed a 5.06% RMSE improvement over the BiLSTM and a 4.968% RMSE improvement over the GRU model for the testing data set. Overall, these findings demonstrated that a deep learning method for calculating the weather forecast.

CONFLICT OF INTERESTS

None.

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