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Generating Spatial Distribution and Forecasting the Rainfall by Suitable ML Models-A Case Study of Aiyar River Basin, Tiruchirappalli District

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Abstract. Rainfall plays a prominent role in managing of water resources. The accurate prediction of rainfall is the greatest challenge in the field of hydrologic studies. The prediction of rainfall is necessary to overcome natural disasters like flood and drought. The inaccurate prediction of rainfall causes either dry or overflow in water storage structures. In this study different types of Machine Learning (ML) and deep learning techniques are adopted to predict rainfall pattern of Aiyar river basin, in Tiruchirappalli district. The comparative study of these ML models is done to identify the best ML model for the study area. The comparison was done for different scenarios and time intervals. The rainfall data from years 1987 to 2023 is used for predicting the daily rainfall in the basin. The rainfall data from years 1987 to 2007 is used for testing and the remaining years data is used for training the data set. The Theisen polygon method is used to average and weighted the rainfall data in the basin. The ML models and deep learning techniques used in this study are Linear model, Support Vector Machine (SVM) and Long Short-Term Memory (LSTM) models. The rainfall was predicted for different time scenario by using different ML algorithms like Autocorrelation method. The accuracy of the predicted model results was tested with RMSE, MASE and R square values. The result shows coefficient between 0.5 to 0.9 within the limit from the daily rainfall values. From the overall model comparison, it is observed that the SVM model accuracy is high compared to the other models involved in this study. It is concluded that two different methods ML and deep learning methods have been applied with same data in which SVM ML techniques gives better results in this study area. In future the predicted rainfall data of this study can be used for accurate flood forecasting and modelling of Aiyar basin.

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Key Words: Rainfall Prediction, Arc-GIS, ML Techniques, SVR, Aiyar basin

1 Introduction

Rainfall is the primary source of water as it is elixir on life of the earth and the most influential hydrological parameters in our day-to-day life. The increase in population, agricultural demand, industry, and livestock made necessity for proper prediction and management of water resources. The accurate prediction of rainfall is essential for the proper planning and management of water resources for the agricultural, domestic, and industrial needs.

The knowledge on rainfall prediction is the subject of extensive research as it is mostly of time bound series data. The time series data can be utilized effectively for predictions in weather and climate change data. In recently due to climate change and human induced environmental activity made the impact on rainfall intensity and it becomes more complicated in prediction.

It is necessary to predict extreme rainfall events for accurate prediction of hydrologic extremes flood and drought [1, 2]. The flood impact makes damage to infrastructure, transport network and in socio-economic status [3]. The drought has a long-term impact on agricultural, hydroelectric power generation and in food security. So suitable prediction models are required for estimating these hydrological impacts.

The weather prediction models such as empirical models, numerical techniques, statistical model, ensemble weather and Numerical weather prediction (NWP) models are also used for rainfall prediction, but these methods are less capable of detecting the hidden patterns or non-linear trends in rainfall data. The NWP models depend on mathematical modelling for data sets, and further on the present climatic factors, but these factors which cannot be directly equipped and to be integrated with parametric equations [4].

The empirical models are study area specific, while the frequency analysis methods are more data oriented. In the statistical model large historical rainfall data with time series is required and the prediction is also based on the historical features. If any data voids are in these techniques the percentage of error is more in predicting the data. The ensemble weather forecasting models are used for predicting the rainfall based on various initial conditions as it must run multiple times to attain outcome in rainfall prediction. In ensemble model complexity are seen during computations.

[5] There are many models being used nowadays, both government and private models. For instance, the Global Forecast System (GFS) is a numerical weather prediction model produced by the National Center for Environmental Prediction-National Oceanic and Atmospheric Administration (NCEP). The autoregressive model, the autoregressive moving average (ARMA) model and the autoregressive moving integrated average (ARIMA) model also been widely used for hydrological series predicting [6]. But these models require more time for calculation and large data sets.

To overcome these limitations advanced modeling methods are required for rainfall prediction one such methods are ML and deep learning techniques [7, 8, 9]. The accurate rainfall prediction is now a challenging task due to extreme climate variations. To improve accuracy in prediction and to overcome limitations from conventional methods ML and deep learning techniques are used for predicting the rainfall. ML and deep learning technique is a promising tool in rainfall prediction. In recent times there has been a growing interest in adopting ML techniques in hydrological sciences and water resources. The advantages of ML techniques are independent on the physical laws of atmospheric processes.

In ML and deep learning techniques the computers can be trained to understand the possible correlation between different variables from the large data set. Its performance is high when compared to conventional rainfall prediction models. ML algorithms have attained wider acceptance in several research domains and there are different ML and deep learning techniques are available for prediction of rainfall in regional as well as global levels. The ML techniques can produce more accurate result by establishing a structural relationship between various parameters [10]. The decision trees, *k*-nearest neighbours, linear regression, and rule-based methods are some of the ML algorithm used for rainfall prediction [11]

2 Related Works

[12] Compared the effectiveness of SVR and random forest (RF) from the radar-derived rainfall forecasting in three reservoir catchments of Taiwan and found that SVR was more accurate in prediction of rainfall. [13, 14] have used ML techniques for various parameters in predicting daily streamflow using multi-layer perceptron (MLP) [18] and Artificial Neuro-Fuzzy Inference System (ANFIS) with shuffled frog-leaping algorithms (SFLA) [15].
[16] Predicted rainfall data in Tasik Kenyir, Terengganu by comparing several ML models by evaluating with different scenarios and time horizon. [17] Developed a deep learning approach for forecasting the precipitation. [18] Predicted short term rainfall by using a convolutional 3D GRU (Conv3D-GRU) model from the machine learning perspective.
[19] Employed the Gaussian Process Regression (GPR) approach in a long time-series rainfall data for identifying the extreme and light rainfall days for 116 years in Sri-harikota in India. [20] Used Machine learning algorithms of ARIMA Model (Auto Regressive Integrated Moving Average), Artificial Neural Network (ANN), Logistic Regression, SVM and Self Organizing Map for rainfall prediction.
[21] Developed a weather forecasting system using modern neural networks and adopted a suitable ML technique of LSTM, TCN and compare its performance with conventional machine learning techniques, statistical forecasting models and dynamic ensemble method.
[22] Adopted an ensemble learning model based on a stacking approach. Four prevalent ML models, namely k-nearest neighbours (KNN), extreme gradient boosting (XGB), SVR, and (ANN) were taken as base models.
[23] Proposed Cluster wise Linear Regression technique for predicting the monthly rainfall in Victoria, Australia. [24] Used two forecasting models for rainfall prediction where the first model predicted for 1 month ahead and the second model is used for predicting 2 months ahead by using ANN. [25] adopted a LSTM-based prediction model for forecasting Jimma's daily rainfall in south-western Oromia, Ethiopia.
In India mostly used ML techniques for rainfall predictions are Regression, ANN, Decision Tree algorithm and Fuzzy logic. [26] Used supervised machine learning techniques like decision tree, Naïve Bayes, K-nearest neighbours, and SVM with fuzzy logic for effective rainfall prediction.
[27] Predicted the rainfall in Taiwan by using the Deep ESN and further it can be improved by using ESN, the BPN and the SVR. [28] Applied three machine learning methods such as SVM, GEP, and MT for the prediction of Standardized Precipitation Index (SPI), Standardized Streamflow Index (SSI), and Standardized Precipitation Evapotranspiration Index (SPEI).
[29] Estimated missing flow data via Random Forest (RF) and K-Nearest Neighbourhood (KNN) methods in their study. [30] Used recurrent neural networks (RNN) and LSTM techniques for improving the rainfall prediction and compared it with random forest and XG boost techniques. [31] Applied data mining techniques for rainfall runoff modeling due to lack of sufficient memory and this issue is solved by a deep-learning-based LSTM model and its performance is compared with RF data-driven model.

In recently deep learning techniques are used to analyse meteorological big data, one of the robust techniques for weather prediction [32]. [33] Proposed a comparative analysis using simplified rainfall estimation models with conventional ML algorithms and Deep Learning architectures that are efficient for these downstream applications.

From the various literature survey, it is inferred that only a few studies were done to compare ML techniques delivered data accuracy with deep learning techniques. In India most of the studies related to rainfall prediction were done separately either by ML or deep learning techniques. It is also limited only to urban basins and more attention is required for a rural basin. Hence the present study aims to develop and compare predicted rainfall data from ML and deep learning techniques in Aiyar basin. The study also determined the most accurate and reliable ML and deep learning model for the chosen study area and also enhance the proper water resources management and forecasting systems of hydrologic extremes.

3 Motivation of the study

The Aiyar basin located in the Tiruchirappalli district is a rural basin and one of the fastest urban areas in Tiruchirappalli city. The extreme rainfall event that happened on the year 2005 necessitates to predict accurate rainfall for managing hydrologic extremes like flood and drought. The year 2005 extreme rainfall has its effect on economic, agriculture and in water resources. For accurate flood prediction necessitates the accurate rainfall prediction. In previous studies flood frequency analysis and statistical methods were used for predicting the rainfall return period in Koraiyar river basin in Tiruchirappalli district [34]. The conventional methods for rainfall prediction shows the deviations in rainfall-run off correlation. So, for proper prediction of rainfall and to minimize the hydrological impacts due to extreme rainfall events, ML and deep learning techniques are used in Aiyar basin. Despite good progress of ML and deep learning techniques, this is the first ML and deep learning study conducted in Aiyar basin.

4 Study Area:

The Aiyar basin a sub-basin of Cauvery River basin passes through the Tiruchirappalli district, Tamil Nadu as shown in Fig.1 The study area lies between the latitude and longitude of 11º30'N and 78º40' E. The basin has two administrative regions Musiri and Thuraiyur. The basin also consists of Kolli and Pachamalai hills. The geomorphology of the basin are Pedi plains, alluvial plains, structural hills, residual hills, valley fills, pediments, buried pediments and upland plateau with undulating plain. The geology of Aiyar basin includes alluvium, laterite, granite dolerite, quartzite, charnockite, granite gneiss, sandstone, and limestone. The basin consists of black cotton soils, red sandy to loamy soils, alluvial soils, sandy soil, sandy loam, red loam, clay, clay loam, black soil, brown soil, and mixed soil. The average rainfall of the basin varies from 750 mm to 890 mm. The basin usually receives more than 100 mm in a day as shown in Fig.1.

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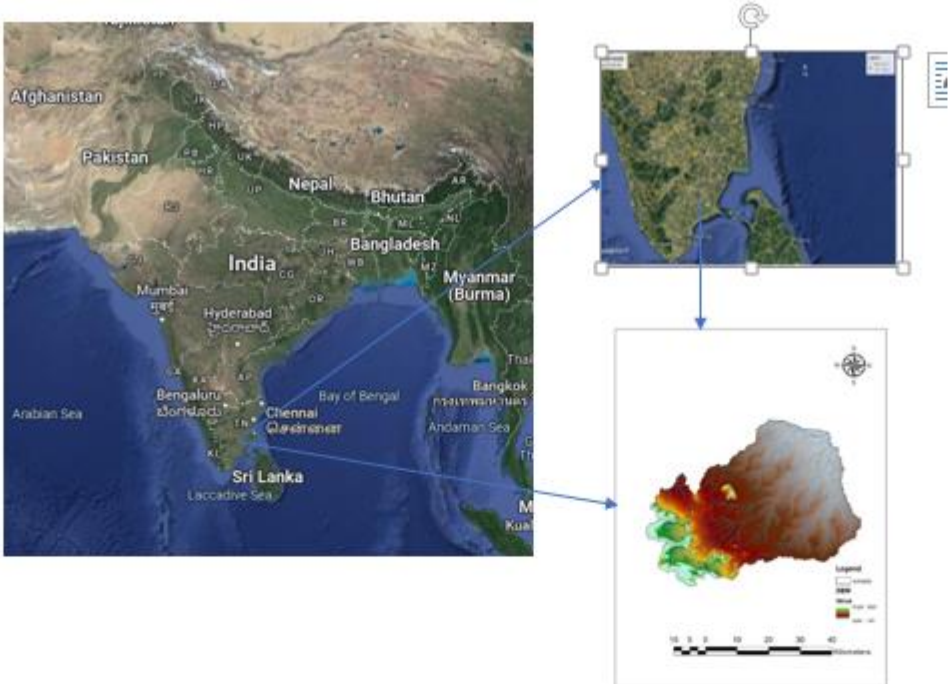


Fig.1. Study Area Digitization

5 Methodology

The proposed methodology adopted for the present study is shown in Fig.2.
The rainfall data for the Aiyar basin is collected from the State Surface and groundwater data centre, Chennai for the years 1978-2015. The trend analysis of rainfall is done to identify the existing trend of the rainfall. The collected rainfall is analysed to remove data voids from the rainfall data. The proposed system forecasts rainfall with two ML and deep learning techniques. The spatial pattern of rainfall and slope map is generated from ArcGIS software. The linear model, SVR, ANN and LSTM techniques were used for getting more accurate results. The sequential steps involved in the study are data entry, pre-processing of data, data division, algorithm training, data set checking and comparison between the algorithms.

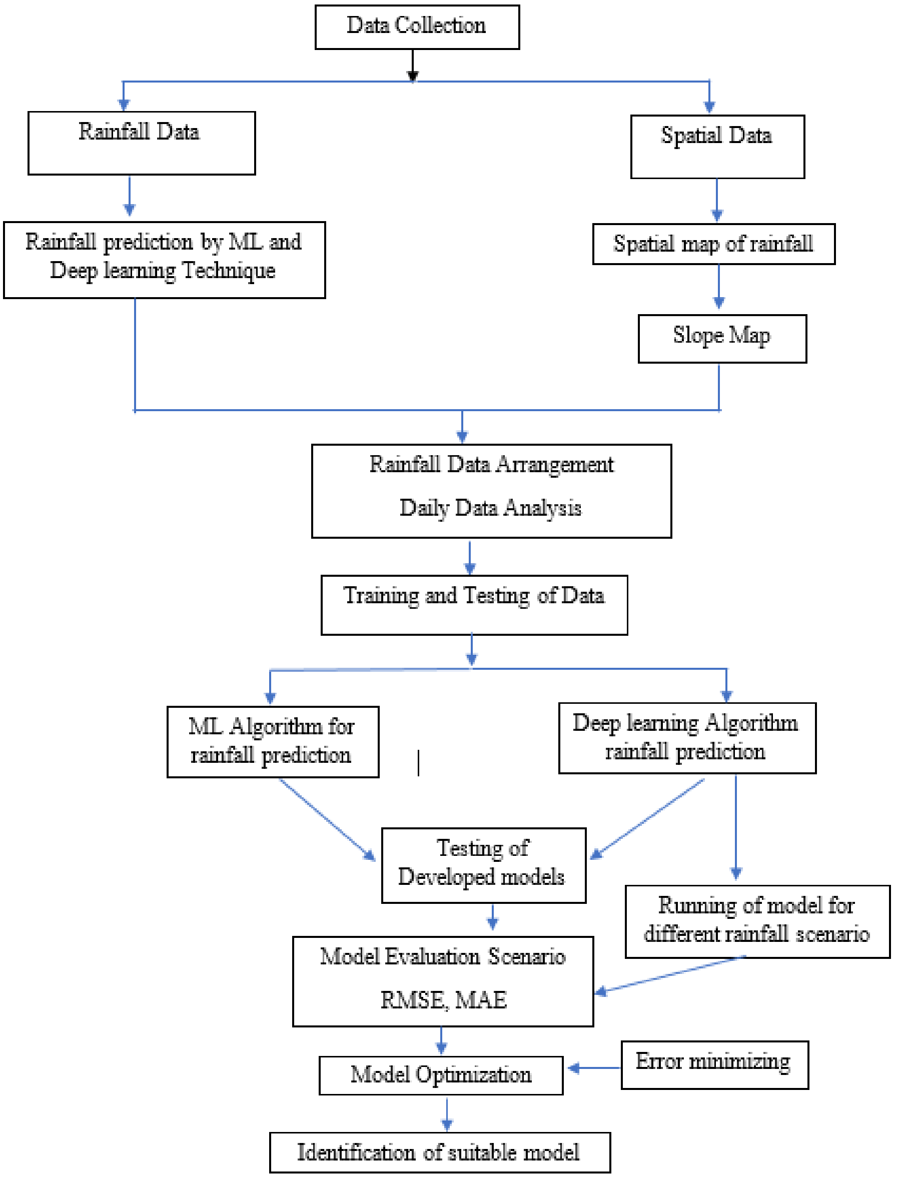


Fig.2. Proposed Methodology of The Study

6 Rainfall Trend Analysis

The trend analysis of rainfall trend analysis is done for the years 1977 to 2015 as shown in Fig.3. The minimum and maximum rainfall experienced in the study area are 242.5 mm to 767 mm as shown in Table.1. From the trend analysis an increasing trend is observed from 1979 to 1984. Similarly, an increase in trend is observed from the years 1991 to 2000. From

2001 onwards the decrease in trend of rainfall is observed. The increase and decrease of rainfall trend are due to existing seasonal variations in the study area.

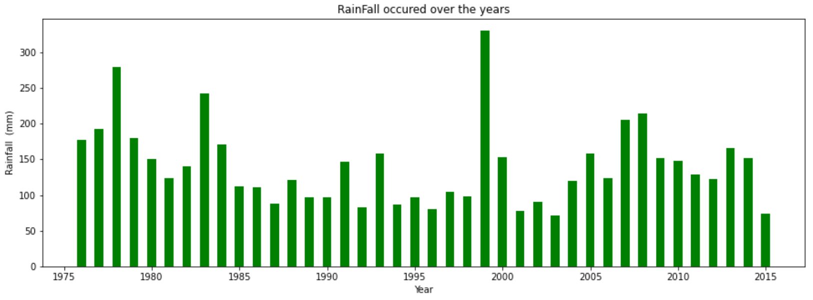


Fig.3. Rainfall Trend-Aiyar Basin

Table 1. Statistical Measures of Rainfall

Station	Mean (mm)	S.D (mm)	Range	Minimum RF (mm)	Maximum RF (mm)
Aiyar basin	767	16.54	110	77	242.5

7 Spatial Pattern of Rainfall

The average spatial pattern of rainfall generated for the Aiyar basin is shown in Fig.4. The spatial map is generated from Arc-GIS by Spatial interpolation techniques through Inverse Distance Weight Method (IDM). The generated spatial rainfall map gives the average of maximum and minimum rainfall distribution in the basin area.

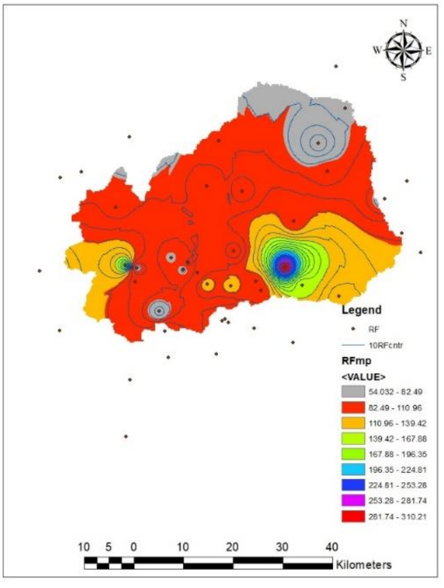
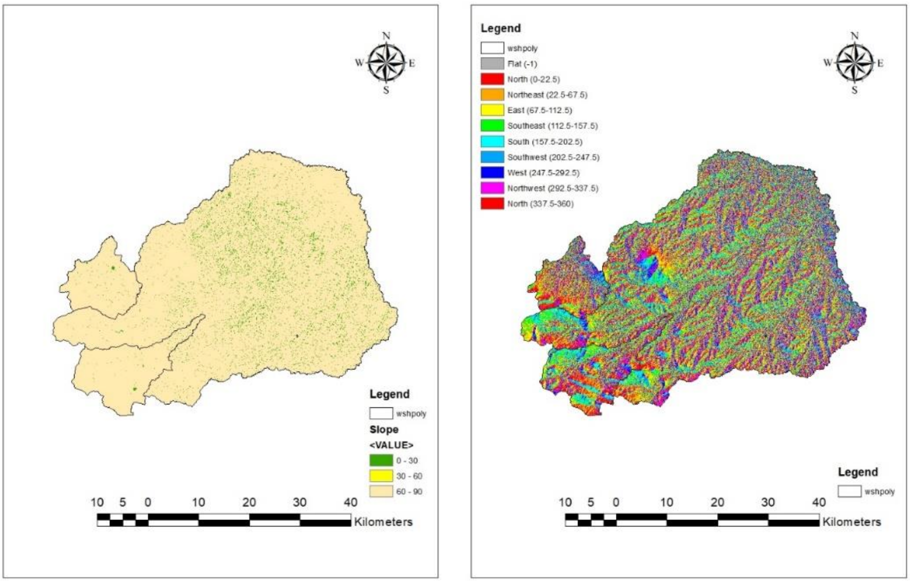


Fig.4. Spatial Distribution of Rainfall Pattern in Study Area

8 Slope

The slope and aspect map developed for the study area as shown in Fig.4. The slope map is generated to identify the slope factor influences in direction of rainfall. The slope less than 3% has lesser influence in the rainfall direction and more than 15% has influence on the rainfall pattern. The aspect ratio is position of terrain as its effects are noted in precipitation direction and the sunshine hours. In this study the aspect is taken for all eight directions.



(a) (b)

Fig.5. (a) Slope Map (b) Aspect ratio

9 Pre-Processing of Data

The pre-processing dataset is the first step in the classification structure that confirms the consistency of extraction performance. The classification structure is used to predict rainfall, in which the data set was cleaned and structured before processing. The cleaning of data is done to work with the missing attributes. The cleaning of data is essential for a better classification operation. The cleaned data is to be tested, trained before pre-processing and simulation process and it must be predicted using an algorithm in modelling before analysis.

10 Data Pre-processing Stages

The data adopted in this study is made into a simple format so that it is formatted in data framework or in machine understanding format. The formatted data is then imported into CSV file. So that algorithm can read the file and continue the process. In case of any missing data format and remove the null values. The data missing places can be replaced with the mean values for the better results. The data is chosen as independent variables or feature column data base, as represented by X. The target or dependable variable rain as Y. The data is splitted into two types as tested and trained data set. The maximum and minimum data are used for testing and training purpose. The data splitting depends upon the form and data size.

11 Adopting Algorithms

The training data is a part of data base used to train the algorithms while the remaining test data from the data are dependent and independent variables. The fit function is adopted to train the model and once fitted the adopted algorithms will use the test data to predict the outcomes as per its process. The predicted rainfall results are generated in binary form 1 or 0 with yes or no options.

12 Accuracy Assessment of Predicted Results

The daily rainfall data is collected for predicting the future rainfall events as shown in Table.2. The rainfall data is predicted for monthly and daily wise, and predicted accuracy is tested by statistical measures. Initially the rainfall is predicted for the existing data and its accuracy is verified by statistical measures Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) to assess the adopted ML algorithms used for this study. RMSE and MAE are widely used methods for measuring accuracy of continuous hydrologic variables as shown in Equation 1 and 2. The MAE it measures the average magnitude of errors of forecasted data.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(E_i - O_i)}{n}} \quad (1)$$

Where Oi is the observed values, Ei is the predicted values and N is the number of observations.

Table 2. Average and Projected Rainfall

Description	Mean (mm)	Standard Deviation (mm)	Minimum (mm)	Maximum (mm)	Median (mm)	Total of Daily Data
Actual Rainfall	767	17.52	77	243.5	9	14600
Predicted Rainfall	765.56	16.66	76.3	243.12	8.56	14600

The RMSE is a quadratic score rule measures the average magnitude of data error. It is square root of the average square difference between observed and predicted results. It gives more weightage to high errors and can be used in data having more error. The MAE and RMSE can be integrated to reduce the error from the predicted results. Mostly RMSE will always be greater than MAE and the more difference between these yields more error differences. To reduce errors MAE must be equal to RMSE.

$$MAE = \frac{\sum_{i=1}^{n} |E_i - O_i|}{n} \quad (2)$$

Oi is the observed values and Ei is the predicted values.
N is the number of observations
The Relative Absolute Error (RAE) method as shown in Equation (3) is also used to check the accuracy of predicted rainfall results. The RAE is the absolute error, and it is relative absolute difference between the actual and the predicted results.

$$RAE = \frac{\sum_{i=1}^{n}|E_i - O_i|}{\sum_{i=1}^{n}|E_i - O_i|} \quad (3)$$

The Root Square Error (RSE) shown in Equation (4) normalize the entire square error of the predicted rainfall values.

$$RSE = \frac{\sum_{i=1}^{n}(E_i - O_i)^2}{\sum_{i=1}^{n}(E_i - O_I)^2} \quad (4)$$

The co-efficient of determination adopted in this study shows the performance of the predicted model in which zero means the random model and 1 means the predicted model is fit.

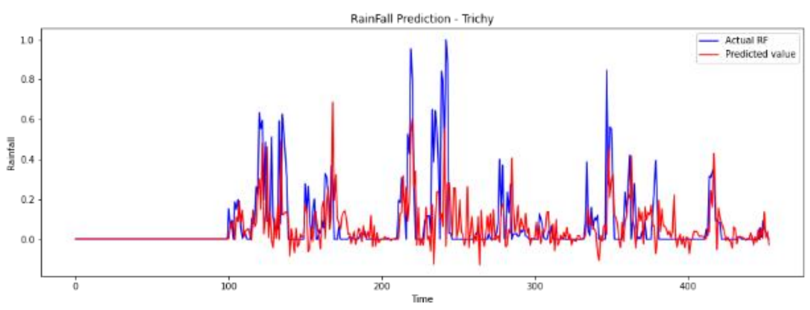
$$R^2 = \frac{\sum_{i=1}^{n}(MSL_o - MSL_o(avg)(MSL_p - MSL_p(avg)}{\sqrt{\sum_{i=1}^{n}(MSL_o - MSL_o(avg))^2 \ \sum_{i=1}^{n}(MSL_p - MSL_p(avg))^2}} \quad (5)$$

13 Prediction of rainfall using projected error

The accuracy measurement of each model is shown in Table. 3. The normalization techniques such as Z score, log normal and min-max of data are used to identify the model accuracy. The model performance analysis shows that log Normal gives better results for monthly and daily prediction of rainfall. The accuracy assessment of the model shows about an R value of 0.3 an acceptable level. The acceptable level of accuracy can be achieved by predicting data for observed values, so that predicted accuracy of existing values can be checked. Finally, the future prediction of rainfall data can be done. The Fig.6. shows the actual values of simulated and predicted rainfall values under various scenarios.

Table 3. ML models Performance Measurements

Regression	Statistical Methods	Training in (%)	MAE	RMSE	RAE	RSE	R
ANN-Daily	Log Normal	90	0.1112	0.1441	0.45	0.33	0.71
ANN-Monthly	Log Normal	85	0.0936	0.1321	0.36	0.29	0.74



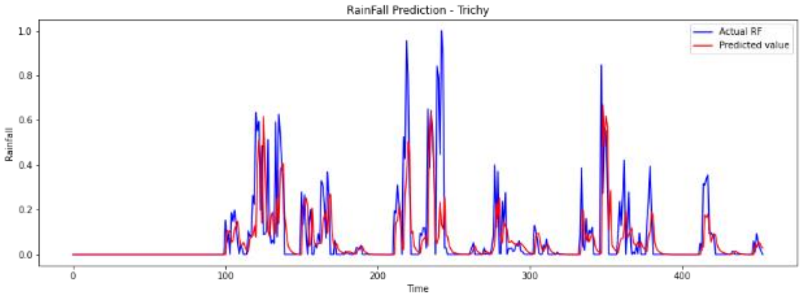


Fig.6. Actual VS Predicted Rainfall of Aiyar Basin

14 Results & Discussions

This study was intended to identify the relevant parameters responsible for intensity of rainfall. The Arc-GIS along with ML techniques were used to predict the rainfall pattern in the study area from year 1977 to 2021. The spatial rainfall pattern map of Aiyar basin is created through Arc-GIS process. In this study ML models used rainfall feature as input algorithm and were implemented in python. The two ML and two deep learning techniques were used for rainfall prediction. The predicted rainfall results from ML and Deep learning models were compared.
Since the data is from the years 1977 to 2015, the rainfall values greater than 0.1 mm is also considered for prediction. The ML and deep learning models of linear model, SVR, ANN and LSTM were used for predicting rainfall under various scenario. From the various scenario ANN model gives better predicted rainfall results when compared with other models adopted in this study. The ANN has highest co-efficient of determination R as shown in Table.4. Initially the prediction of rainfall from the ML models did not perform well without tuning the data and after tuning the data improvements are seen while predicting the rainfall. The better accuracy of the predicted results is judged from the statistical measures of the developed model. The statistical co-efficient of the predicted results ranges from 0 to 0.3 which means the better statistical fit is achieved. The obtained predicted results can be used for further applications. The statistical fit for linear model is 0.24, SVR is exactly 0.2, followed by LSTM 0.21. For ANN the RMSE is 0.25 which is higher than other three methods. The RMSE ranges from 0.3 to 0.5 of the best fit, so the predicted accuracy is more than other methods. Hence based on the predicted results it can be concluded that ANN can predict the rainfall at various scenario with acceptable level of accuracy. Further the accuracy of model can be improved when more inputs are added.

Table 4. Results of the adopted ML model before and after the tuning

Scenario	Regression	Model	Coefficient of Determination
Daily	ANN	Without tuning	0.21
Monthly	ANN	With tuning	0.30

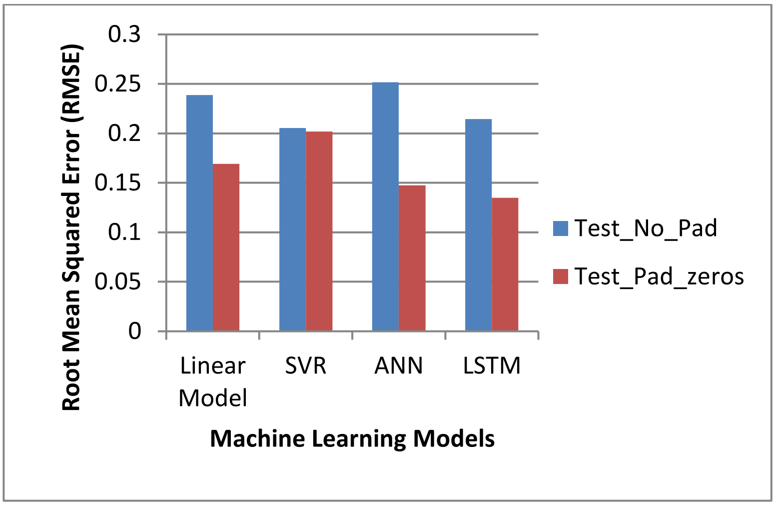


Fig.7. Comparison of Adopted ML Techniques-Aiyar Basin

15 Conclusions

Rainfall distribution and prediction is necessary for managing the hydrologic extremes flood and drought. This paper focuses on generating spatial rainfall maps and predicting rainfall by using ML techniques for Aiyar river basin, Tiruchirappalli district. The historical rainfall data were collected from year 1977 to 2015. The spatial rainfall map and prediction of rainfall were done from the existing historical rainfall data as well as projected error-based method. For prediction of rainfall ML and deep learning models like Linear model, SVR, ANN and LSTM were used to predict rainfall for different scenarios of monthly and daily basis. The accuracy assessment for each predicted model is done through statistical measures. The RMSE of the developed ML and deep learning models ranges from 0 to 0.3. The ANN has the maximum value of 0.3 the highest co-efficient of determination in compared to other three models used in this study, which means predicted results are better than other methods. The proposed study can be used if conditions exist in other areas.

The following conclusions are made from the study.

- The more input data can be added to improve the developed ML models.
- The ANN model predicted the rainfall data with higher accuracy.
- Hybrid ML algorithms can also be used for predicting data for getting higher accuracy.

Future Scope of the work

- The predicted rainfall data accuracy can be improved by incorporating sensor data.
- It is recommended to use big data with sensors for daily rainfall data prediction.
- The predicted rainfall can be used for simulating flood and drought under various scenarios.

References

1. Goswami B N, Venugopal V, Sengupta D, Madhusoodanan M S and Xavier P K 2006 Increasing trend of extreme rain events over India in a warming environment; Science 314 1442–1445, https://doi.org/10.1126/science.1132027.

2. Rajeevan M, Bhate J and Jaswal A K 2008 Analysis of variability and trends of extreme rainfall events over India using 104 years of gridded daily rainfall data; Geophys. Res. Lett. 35 L18707, https://doi.org/10.1029/2008GL035143.
3. Le, TT., Pham, B.T., Ly, HB., Shirzadi, A., Le, L.M. (2020). Development of 48-hour Precipitation Forecasting Model using Nonlinear Autoregressive Neural Network. In: Ha-Minh, C., Dao, D., Benboudjema, F., Derrible, S., Huynh, D., Tang, A. (eds) CIGOS 2019, Innovation for Sustainable Infrastructure. Lecture Notes in Civil Engineering, vol 54. Springer, Singapore. https://doi.org/10.1007/978-981-15-0802-8_191
4. Balamurugan, M.S., Manojkumar, R. Study of short term rain forecasting using machine learning based approach. *Wireless Netw* **27**, 5429–5434 (2021). https://doi.org/10.1007/s11276-019-02168-3
5. Azevedo, A.I.R.L.; Santos, M.F. KDD, SEMMA and CRISP-DM: A Parallel Overview. In Proceedings of the IADIS European Conference Data Mining, Amsterdam, The Netherlands, 24–26 July 2008; pp. 182–185.
6. Valipour, M.; Banihabib, M.E.; Behbahani, S.M.R. Comparison of the ARMA, ARIMA, and the autoregressive artificial neural network models in forecasting the monthly inflow of Dez dam reservoir. J. Hydrol. 2012, 476, 433–441.
7. Schneider, T., Lan, S., Stuart, A., & Teixeira, J. (2017). Earth system modeling 2.0: A blueprint for models that learn from observations and targeted high-resolution simulations. *Geophysical Research Letters*, *44*(24), 12-396.
8. O'Gorman, P. A., & Dwyer, J. G. (2018). Using machine learning to parameterize moist convection: Potential for modeling of climate, climate change, and extreme events. *Journal of Advances in Modeling Earth Systems*, *10*(10), 2548-2563.
9. Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat, F. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), 195-204.
10. Lam, H. K., Ling, S. H., Leung, F. H. F., & Tam, P. K. S. (2001). Tuning of the structure and parameters of neural network using an improved genetic algorithm. In IECON'01. 27th annual conference of the IEEE industrial electronics society (Cat. No.37243), Denver, CO, USA (Vol. 1, pp. 25–30).
11. Xue Y., Jiang J. & Hong L. 2020 A LSTM based prediction model for nonlinear dynamical systems with chaotic itinerancy. International Journal of Dynamics and Control 8, 1117–1128.
12. Yu, P.-S.; Yang, T.-C.; Chen, S.-Y.; Kuo, C.-M.; Tseng, H.-W. Comparison of random forests and support vector machine for real-time radar-derived rainfall forecasting. J. Hydrol. 2017, 552, 92–104. [CrossRef]
13. Mohammadi B, Ahmadi F, Mehdizadeh S, Guan Y, Pham QB, Linh NTT, et al. Developing novel robust models to improve the accuracy of daily streamflow modeling. Water Resour Manag 2020.
14. Ahmadi, M., Sharifi, A., Dorosti, S., Ghoushchi, S. J., & Ghanbari, N. (2020). Investigation of effective climatology parameters on COVID-19 outbreak in Iran. *Science of the total environment*, *729*, 138705.
15. Mohammadi B, Linh NTT, Pham QB, Ahmed AN, Vojteková J, Guan Y, et al. Adaptive neuro-fuzzy inference system coupled with shuffled frog leaping algorithm for predicting river streamflow time series. Hydrol Sci J 2020:1.
16. Wanie M. Ridwan, Michelle Sapitang, Awatif Aziz, Khairul Faizal Kushiar, Ali Najah Ahmed, Ahmed El-Shafie, Rainfall forecasting model using machine learning methods:

Case study Terengganu, Malaysia, Ain Shams Engineering Journal,12, 2021, 1651-1663. https://doi.org/10.1016/j.asej.2020.09.011.

17. Yan Q, Ji F, Miao K, Wu Q, Xia Y and Li T 2020 Convolutional residual-attention: A deep learning approach for prediction of nowcasting; Adv. Meteorol., https://doi. org/10.1155/2020/6484812.
18. Dechao Sun, Jiali Wu, Hong Huang, Renfang Wang, Feng Liang, Hong Xinhua, "Prediction of Short-Time Rainfall Based on Deep Learning", *Mathematical Problems in Engineering*, vol. 2021, Article ID 6664413, 8 pages, 2021. https://doi.org/10.1155/2021/6664413
19. Subrahmanyam, K.V., Ramsenthil, C., Girach Imran, A. *et al.* Prediction of heavy rainfall days over a peninsular Indian station using the machine learning algorithms. *J Earth Syst Sci* **130**, 240 (2021). https://doi.org/10.1007/s12040-021-01725-9
20. C. Z. Basha, N. Bhavana, P. Bhavya and S. V, "Rainfall Prediction using Machine Learning & Deep Learning Techniques," *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2020, pp. 92-97, doi: 10.1109/ICESC48915.2020.9155896.
21. Hewage, P., Trovati, M., Pereira, E. *et al.* Deep learning-based effective fine-grained weather forecasting model. *Pattern Anal Applic* **24**, 343–366 (2021). https://doi.org/10.1007/s10044-020-00898-1
22. Gu, J.; Liu, S.; Zhou, Z.; Chalov, S.R.; Zhuang, Q. A Stacking Ensemble Learning Model for Monthly Rainfall Prediction in the Taihu Basin, China. Water 2022, 14, 492. https://doi.org/10.3390/ w14030492
23. Bagirov, A.; Mahmood, A.; Barton, A. Prediction of monthly rainfall in Victoria, Australia: Clusterwise linear regression approach. Atmospheric Res. 2017, 188, 20–29. [CrossRef]
24. Mishra, N.; Soni, H.K.; Sharma, S.; Upadhyay, A.K. Development and Analysis of Artificial Neural Network Models for Rainfall Prediction by Using Time-Series Data. Int. J. Intell. Syst. Appl. 2018, 10, 16–23.
25. Demeke Endalie, Getamesay Haile, Wondmagegn Taye; Deep learning model for daily rainfall prediction: case study of Jimma, Ethiopia. *Water Supply* 1 March 2022; 22 (3): 3448–3461. doi: https://doi.org/10.2166/ws.2021.391
26. Rahman, A.-u.; Abbas, S.; Gollapalli, M.; Ahmed, R.; Aftab, S.; Ahmad, M.; Khan, M.A.; Mosavi, A. Rainfall Prediction System Using Machine Learning Fusion for Smart Cities. Sensors 2022, 22, 3504. https://doi.org/10.3390/s22093504
27. Yen, MH., Liu, DW., Hsin, YC. *et al.* Application of the deep learning for the prediction of rainfall in Southern Taiwan. *Sci Rep* **9**, 12774 (2019). https://doi.org/10.1038/s41598-019-49242-6
28. Shamshirband, S., Hashemi, S., Salimi, H., Samadianfard, S., Asadi, E., Shadkani, S., Kargar, K., Mosavi, A., Nabipour, N., & Chau, K.-W. (2020). Predicting standardized streamflow index for hydrological drought using machine learning models. Engineering Applications of Computational Fluid Mechanics, 14(1), 339–350. https://doi.org/10.1080/ 19942060.2020.1715844
29. Ozen, H., & Bal, C. (2020). A study on missing data problem in random Forest. Osmangazi Journal of Medicine, 42(1), 103–109. https://doi.org/10.20515/otd.496524
30. T., ASS, Somula, R, K., G, Saxena, A, A., PR. Estimating rainfall using machine learning strategies based on weather radar data. *Int J Commun Syst*. 2020; 33:e3999. https://doi.org/10.1002/dac.3999

31. Chengcheng Chen, Qian Zhang, Mahsa H. Kashani, Changhyun Jun, Sayed M. Bateni, Shahab S. Band, Sonam Sandeep Dash & Kwok-Wing Chau (2022) Forecast of rainfall distribution based on fixed sliding window long short-term memory, Engineering Applications of Computational Fluid Mechanics, 16:1, 248-261, DOI: 10.1080/19942060.2021.2009374
32. D. Attali and A. Montanvert, “Computing and simplifying 2D and 3D continuous skeletons,” Computer Vision and Image Understanding, vol. 67, no. 3, pp. 261–273, 1997.
33. Ari Yair Barrera-Animas, Lukumon O. Oyedele, Muhammad Bilal, Taofeek Dolapo Akinosho, Juan Manuel Davila Delgado, Lukman Adewale Akanbi, Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting, Machine Learning with Applications, 7,2022, https://doi.org/10.1016/j.mlwa.2021.100204.
34. Natarajan, S., Radhakrishnan, N. Simulation of rainfall–runoff process for an ungauged catchment using an event-based hydrologic model: A case study of koraiyar basin in Tiruchirappalli city, India. J Earth Syst Sci 130, 30 (2021). https://doi.org/10.1007/s12040-020-01532-8.