

ASSESSING MODELS FOR FORECASTING RAINFALL AND IMPLEMENTING MACHINE LEARNING TECHNIQUES

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Abstract

The best predictive model was determined by comparing three main types. For machine learning algorithms and statistical models, data-driven learning and improvement are automatic processes. To find complex patterns and relationships in data, deep learning uses neural networks. Combining satellite imagery, radar data, and aircraft or satellites allows for ground-based observations, while remote sensing (RS) collects data about distant objects or locations. Radar and satellite-derived regional precipitation data are the foundation of hybrid models. Following that, an algorithm trained on earlier rainfall readings would process the data. The machine-learning model uses remote monitoring input features to predict precipitation. Machine learning regression techniques are evaluated based on the degree of agreement between expected and observed values. Regardless of climate or timescale, machine learning's ability to predict rainfall is a strength among others. As one of the most widely used models for rainfall prediction, the LSTM models show their superiority. This is a cutting-edge technique for calculating rainfall. The deep learning methodology is most useful for implementing this kind of method and determining its accuracy. Memory sequence data measurement is done using a long short-term memory method, which computes historical data quickly and generates the best prediction.

Keywords: Rainfall Forecasting, Hybrid, Mean absolute error(MAE), statistical models, LSTM.

Introduction

The term "rainfall forecast" in meteorology refers to the use of a range of methods to forecast the amount, location, and duration of precipitation in a given area during a predefined period of time. Numerous businesses, such as transportation, energy generation, agriculture, emergency response, and water resource management, depend on weather forecasting. It helps determine when and how much rain will fall. Precipitation forecasts can be supported by conventional ground-based data, remote sensing, and numerical weather models. Rain gauges on the ground are typically used to track rainfall, however remote sensing techniques such as satellites and radar can be used to estimate rainfall. Numerical weather models imitate atmospheric parameters and the anticipated weather for the future patterns through the use of mathematical equations [1]. Forecasting rainfall is essential. By examining rainfall data from the past and projecting rainfall for future seasons. We may employ a range of models, such as regression and classification, based on

the specifications. Additionally, able to calculate the accuracy and inaccuracy between the predicted and real numbers. It's critical to select the appropriate algorithm and model it in accordance with the needs, because different approaches offer differing degrees of accuracy [2,3]. Inaccurate rainfall projections can negatively impact society in a number of areas, including agriculture, disaster preparedness, and infrastructure development. People who rely on weather forecasts should be aware of any potential information gaps, and efforts are being made to improve prediction reliability. By examining and evaluating several recent and earlier research that employed machine learning and remote sensing techniques to predict rainfall, this review paper investigated the distinctiveness and advantages of such projected models.

Methodology

The investigation began with a review of the literature, followed by the collection and analysis of materials related to rainfall forecasting. Scopus is recognized as the most prominent database for scientific studies. For this research, only publications classified as "articles" or "book chapters" were included. Several review papers discussed the application of machine learning models for rainfall prediction. However, a comprehensive comparison between remote sensing methods and machine learning models has yet to be conducted. An analysis of related experiments suggests that the search algorithm is the most crucial and innovative equation for rainfall prediction. The latest studies are accessed using both the IEEE and Scopus databases. The search covers years from 2010 to 2023. Following the database search illustrated in Figure 1.

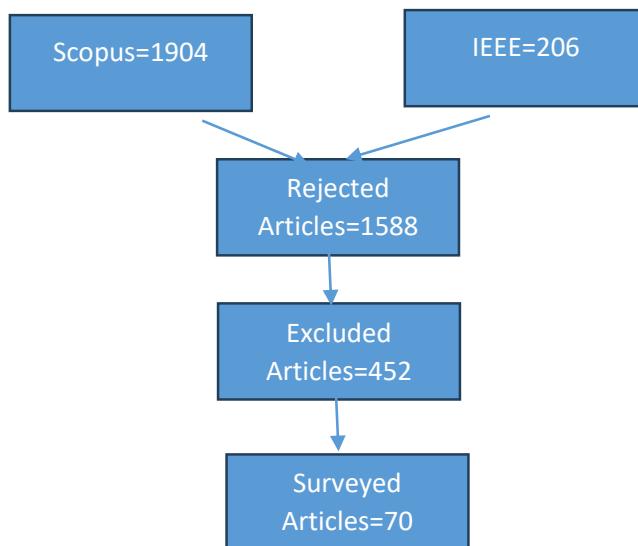


Figure 1: Method for choosing articles

The Scopus database included 1904 papers, while the IEEE database had 206 papers. A total of 1588 papers were disregarded as they were irrelevant to the topic. Additionally, 452 papers were eliminated because they either did not focus on rainfall forecasting with

anticipatory models, were duplicates, or were not readily accessible. After examining relevant papers, an analysis was conducted. A selection of articles was made based on specific criteria according to the following standards:

1. Predicting rainfall is the primary emphasis of the study.
2. Assessment metrics are supplied by the inquiry.
3. The research makes variable predictions.

Table 1: Predicting rainfall through research

AUTHORS	CASE STUDY	INITIAL YEAR	END YEAR	TYPE
[16]	Malaysia	1988	2017	Meteorological
[7]	Indonesia	1981	2020	Meteorological
[6]	China	2018	2019	Meteorological
[9]	India	2010	2014	Meteorological,
[8]	India	1988	2021	Meteorological
[5]	India	2002	2022	Meteorological
[12]	India	2015	2020	Hydrological
[10]	India	1901	2016	Hydrologica
[14]	India	1941	2005	Meteorological
[11]	Thailand	2004	2018	Meteorologica
[4]	Australia	2008	2017	Meteorological
[13]	Australia	1960	2015	Hydrological
[15]	India	2012	2017	Meteorological

To ensure the research remains relevant to the latest findings on this topic, most of the reviewed papers date back to 2022. Table 3 presents a summary of the various studies that were analysed for this work. It includes information on the country where the rainfall forecast model was implemented, the input variable used, and the time period during which the data were gathered..

Categorization of Research:

The numerous types of rainfall forecasting research can be categorized using the several input data formats that the models employ to predict the amount of rainfall. A large number of the studies under review incorporate meteorological or hydrological data as inputs. The input data that were taken into account are shown in Figure 2.

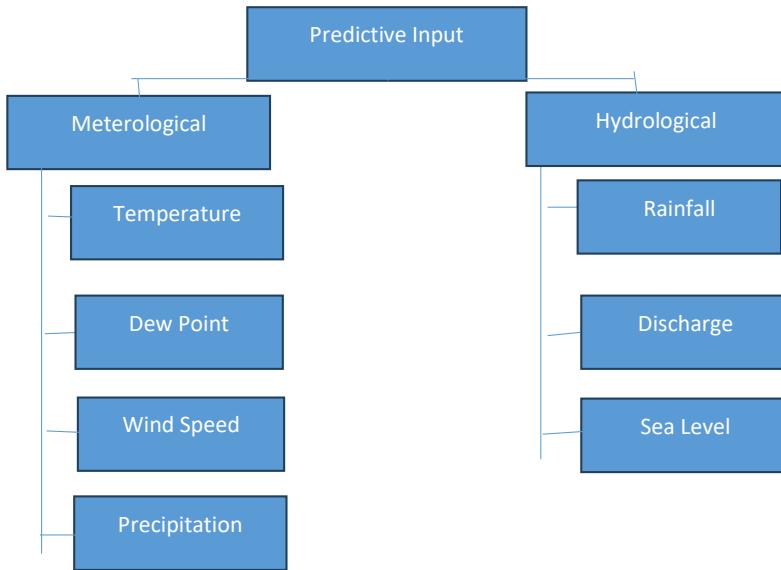


Figure 2: Categories of Forecasting Parameters

Meteorological Contributions

Observational meteorological data measures the following atmospheric conditions: dew point, temperature, cloud layer(s), cloud cover, wind speed, wind direction, precipitation amount, visibility, ceiling height, and weather conditions at the moment. Variations in precipitation are widely predicted using meteorological data. This research reviews about 10 papers that exclusively rely on meteorological data (Table 1). Temperature and humidity are frequently used as input variables in papers from [13–15].

Hydrological Inputs

To achieve satisfactory results in various hydrological modeling approaches, it is essential to collect, analyze, and utilize hydrological data. Hydrological indicators such as outflow and tide levels have been reliably used to forecast precipitation. The referenced papers rely solely on rainfall parameters.

Rainfall Predictive Models

Predictive Rainfall models as shown in Figure 3.

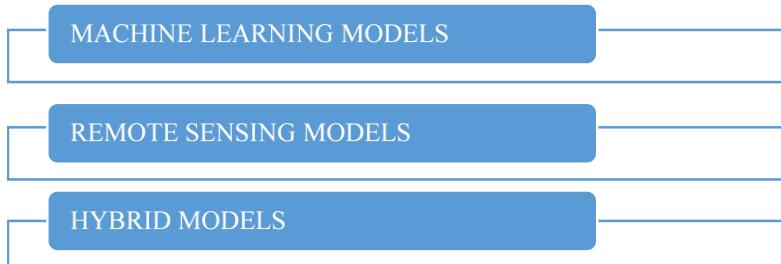


Fig 3: Rainfall Predictive Models

Machine Learning Models

Utilizing statistical models and algorithms, machine learning is a subfield of artificial intelligence that enable an unprogrammed machine to autonomously learn from data and grow. Neural networks are utilized in deep learning, a type of machine learning, to identify intricate patterns and connections in data..Numerous techniques have been used to apply both Deep and Machine learning Techniques to the prediction of rainfall. As an example, The application of machine learning techniques is to determine trends and connections within past precipitation data, which can be leveraged to provide more accurate predictions. There are 35 publications in all that use machine learning (ML) as their rainfall prediction model, according to Table 2. This demonstrates the rise in popularity of this prediction metric over the past few years.

Table 2: Research on models for machine learning

Research Article	Machine Learning Techniques
[17]	ANN
[18]	CNN and ARIMA
[19]	SVR and MLP
[20]	LSTM, MC-LSTM
[21]	KNN,RF and NN
[4]	DCNN
[22]	RR,DNN
[23]	XGB,SVR and ANN
[24]	LSTM
[25]	SVM
[26]	LR,SVM,CNN
[27]	TRU-NET
[28]	ANN
[29]	RF

LSTM:

Long Short Term Memory is a key and modern deep learning algorithm. Recurrent sort memory is the primary component of rainfall time calculation since it allows for data interpretation and precise prediction. There are three basic components in gates: Input, output, and forget gates are the first three gates. With the information flow, we use this gate to determine the forecast prediction. LSTM gates are sigmoid activation functions, meaning they produce values between 0 and 1. "0" indicates that the gates are completely blocked. "1" indicates that gates are opening to let everything go through it. The basic timestamp LSTM Memory circuit model for rainfall prediction is displayed in Figure 4.

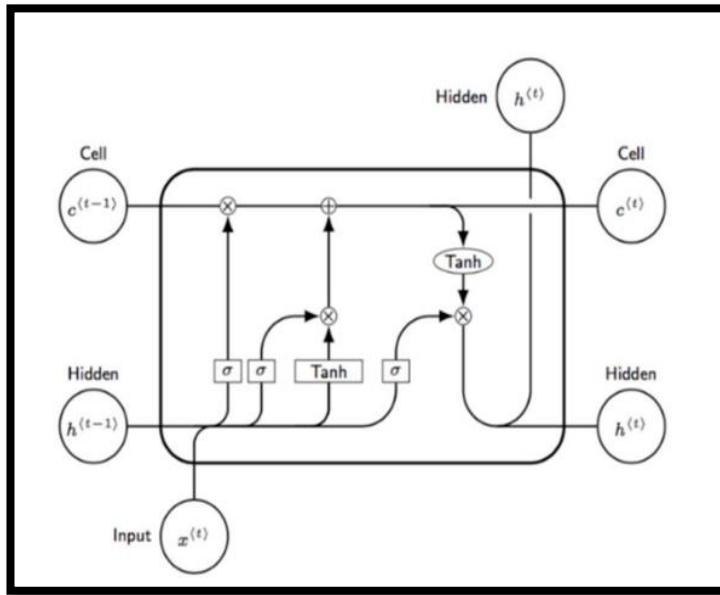


Fig 4: LSTM Memory circuit model for rainfall Prediction

Remote Sensing

The scientific process of collecting data about far-off objects or locations using aircraft or satellites is known as remote sensing (RS). The application of remote sensing to weather forecasting has advantages for agriculture, hydrology, and meteorology [30]. Table 3 lists some remote sensing models that can be used to forecast rainfall. non-active microwave detectors measure the radiation from microwaves that the atmosphere emits in order to detect rainfall. These radars are able to give data regarding the quantity and dispersion of rain falling on a wide area.

Table 3: Research on models for remote sensing.

Research Article	Remote Sensing Models
[23]	TRMM & QM
[12]	GFS
[31]	ESN, Deep ESN
[32]	MJO
[26]	CFSR
[14]	GCM
[13]	FBP

Hybrid Model

While there are certain benefits, there are drawbacks to employing a model that forecasts rain by fusing models for machine learning and remote sensing. When utilizing a combination of remote sensing and machine learning to forecast rainfall, it is imperative to thoroughly assess constraints like, restricted interpretability, low Adaptability to a wider context, absence of openness and poor quality instruction sets. In order to achieve this, time

and financial resources may need to be allocated to the collection and training of superior quality information, Accurate prediction verification of the model, and stakeholder consultation to guarantee the model's suitability for the intended use. Table 4 illustrates how a combination of machine learning and remote sensing techniques often happens when machine learning prediction models are trained with remote sensing data as an input parameter [26].

Table 4: Research on hybrid models

RESEARCH ARTICLE	HYBRID MODELS
[33]	GPS
[34]	MLP,RF
[35]	CGAN
[7]	Convolutional LSTM-AT with ArcGIS

Conclusion

There are various limits and recommendations that were previously discussed because some of the research that was studied in this paper was so thorough and intricate. First, some studies employ performance measurements that are insufficient to properly confirm the prediction models' proven accuracy [16]. Another frequent finding is that some prediction models haven't been contrasted with other models that have already been constructed. This is typically because the authors' primary goal was to demonstrate the applicability of a recently developed model, and they only provided it as a substitute strategy for particular eras or regions. Thus, it is advised that these two categories of prediction models be further investigated in light of the dearth of remote sensing and hybrid models. to employ top-notch, advanced technology, to solve issues for the benefit of a healthy future, to generate more significant discoveries, and to safeguard society. The authors genuinely hope that the findings of this review study would aid in directing further research and enhancing the precision of rainfall forecasting systems.

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