International Journal of Scientific Research & Engineering Trends
Volume 9, Issue 1, Jan-Feb-2023, ISSN (Online): 2395-566X

# A Comparative Analysis of Weather Forecasting Techniques

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**Abstract- The annual rainfall of India has three seasons per year accounting for about 11% each in the pre-monsoon (January-May) and the northeast monsoon (October-December)and 78% in the southwest monsoon season also known as summer monsoon (June-September). The maximum amount of the rainfall occurs during southwest monsoon (SWM), which governs the agricultural economy of India and hence for administrative purposes. While the season recurs annually, the variation about the long term expected value can be as high as 40-50% in some parts of the country. Variability during SWM season is an uncertain quantity which India faces every year. This uncertainty cans be year to year, season to season (within year), month to month (within season and with inyear) and so on depending on the requirement in the practical purposes. The hugevariation in the rainfall causes droughts and floods. The distress caused by droughts and floods due to extreme variations of the monsoon can be mitigated to some extent if the rainfall time series can be modeled efficiently for simulation and forecasting of SWM data. Hence this becomes the primary reason to develop new models for Indian monsoon rainfall. Rainfall data is a strongly non-Gaussian time series exhibiting non-stationarity.The main objective of the present paper is to compare new statistical approaches to model and forecast Indian monsoon rainfall data. The prediction of earthquakes, floods, rainfalls are predicted by linear data using least square methods. However, in reality this data is non-linear and varies over a period of time, therefore these models failed to give exact results. To overcome this disadvantage the researcher has considered the models based on time series together with data mining techniques for effective prediction. Most of the weather data contains hidden patterns, therefore data mining techniques help to identify these hidden patterns more accurately. Therefore it is necessary to predict weather changes more significantly. The proposed work is highlighted in this direction. In this paper, an attempt is made compare weather prediction models based on the spatial and temporal dependencies among the climatic variables together with forecasting analysis.**

**Keywords- Rainfall prediction, Data Science, Data Mining, Forecasting.**

## I. INTRODUCTION

Time Series is termed as a sequence of observations measured at equal intervals of time. The observations are measured hourly, daily, weekly, monthly, yearly or at any other regular interval.

When the observations are recorded continuously through time, time series is said to be continuous and if the observations are recorded at specified times, usually equally spaced, then it is said to be discrete. The dependence among the observations in a time series data is of great interest. Analysis of this dependence is found by using techniques. Forecasting in general can be referred to as the process of estimating or evaluating the value of some variable at some future point of time. Forecasting is an important problem that is used by the government and industry for doing planning and decision making, to protect life and property and by every individual to carry out daily activities. There are two main broad types of forecasting techniques- qualitative techniques and quantitative techniques. Qualitative forecastsare normally used in situations where there is no or little historical data is available. An example being the introduction of a new product for which no history is available whereas quantitative forecasts make use of historical data. In this technique, a forecasting model is used to project the past and current data into the future. If the historical data is restricted to past values the forecasting procedure is called time series method and the corresponding historical data is termed as time series. Analysis of time series mainly deals with statistical methods or any other methods to analyze and extract the characteristics of the given data. Time series analysis aims at identifying the pattern in the given time series and using it to predict the future. A model is constructed to extract meaningful information about the data using appropriate methods. Using the prescribed model, one can forecast the future occurrence based on past data. Three things are essential for the survival of human beings. They are air, food, and water. Water is available in different forms of precipitation. Among them, rain is the most important. Rivers and lakes are considered to be natural resources for any place. Forecasting weather parameters which include rainfall, temperature, wind, humidity, etc. for a region plays an important role and in fact it is one of the main functions of National Weather Services. Information about rainfall is very much useful for predicting natural disasters such as droughts and floods. Rainfall forecasting is also very much helpful to decide upon the area of irrigation, the requirement of water for irrigation, estimating quantity and quality of surface water and groundwater, etc.

Forecasting models help us to understand the meteorological information thereby integrate the information into the planning and decision-making process. Thus, forecasting rainfall acts as an aid for doing efficient planning by the government. The sequence of data analysis based on its types and its functionality is shown in Figure1 as of three major types: Descriptive analytics, Predictive analytics and Prescriptive analytics [5]. From the figure, it is clear that a general understanding of the data is very important before dealing with the data. Hence descriptive analytics is carried out first, next is predictive analytics and finally, prescribing a solution using prescriptive analytics is done.

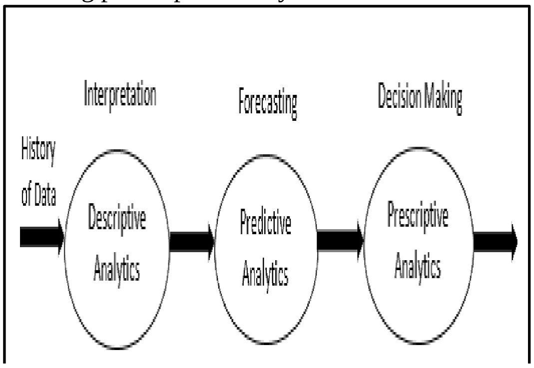


Figure 1: Way towards prescriptive analytics.

### 1. Descriptive Analytics
Descriptive analytics is the anterior process of data analytics that aids in understanding thecurrent state of the scenario and the reasoning behind the event that happened [6]. To carryout descriptive analytics, histories of data are examined and appropriate visualizationtechniques are used to find the facts [7]. Descriptive Analytics is also helpful inunderstanding the changes occurring in the data pattern over time and in figuring out thecomparisons. Besides, it narrates the main features of the data such as mean, standarddeviation, variance, quartiles, sum of squares, Root Mean Square (RMS), frequency, etc.,which are necessary for the subsequent stages of analytics.

### 1.1 Predictive Analytics
Predictive analytics assists in predicting or forecasting future possibilities and outcomes. It is essential to plan for the upcoming period [8]. This stage of analytics is necessary to take preventive measures if the outcomes predicted are detrimental to the intention. Prediction is a general term used to determine the unknown future outcomes whereas fore casting includes a temporal dimension to defend the subsequent outcomes. In the early days, predictive analytics was implemented using statistical methods [9]. Currently, Machine Learning (ML) algorithms and Artificial Neural Networks (ANN) play a predominant rolein carrying out these analytics. Predictive modeling is mostly adopted in classification andclustering problems while the time series data utilizes the forecasting model.

### 1.2 Prescriptive Analytics
Prescriptive analytics is used to prescribe the finest course of action based on the predictedoutcomes [10]. It also emphasizes the inference of recommended action thereby leading tooptimal decision making which will help the society in many aspects. The inference fromprediction may be a favorable or an unfavorable circumstance. Hence the communityneeds knowledge about the action to be taken to handle the situation. Thus prescriptiveanalytics is considered as the esteemed level of analytics. The methodology used to implement prescriptive analytics is typically a blend of techniques such as mathematical programming, logic-based models etc., [11] which may also include predictive analytics occasionally.

### 2. Data Analytics Models for Weather Forecasting
The significance of data analytics and different types of analytics were discussed in the previous section which emphasized the importance of its usage. This section will emphasize more on the algorithms and techniques used to implement them.

### 3. Measures of Descriptive Analytics
Descriptive analytics is used to understand the circumstances using past and present data. Hence it acts as a base for predictive analytics by detecting the interval trends which are helpful to estimate future trends [12]. It uses statistical methods principally to summarize the knowledge patterns that comprise the following measures [13],

- Measures of Central Tendency (Mean, Median and Mode)
- Measures of Dispersion/Variation (Range, Variance and Standard Deviation)
- Measures of Position (Percentile, Lower Quartile and Interquartile)
- Measures of Frequency (Ratio, Rate, Proportion and Percentage)

The above measures are simple. With the help of visualization techniques like probability distribution plot, box plot, scatter plot, histogram and bar chart, these measures will figure out the data patterns apparently.

## II.METHODS FOR PREDICTIVE ANALYTICS

Predictive analytics has gained more attention in the research community when compared to other types of analytics [14]. Probabilistic and progressive statistical methods like Bayesian, Markov Chain and Hidden Markov Chain are mostly used as prediction models[15]. These models help to estimate the likely occurrence of any event in the future and the knowledge inferred is represented through probability distribution [16]. Secondly, advanced statistical methods like regression, Auto Regressive Integrated Moving Average (ARIMA) and Support Vector Machine (SVM) play a major role now in prediction and forecasting. In recent years, machine learning and data mining methods occupy a greater space in the domain of prediction. Our research focus is mainly on ANN for prediction and the subsequent section discusses ANN.

### 1. Artificial Neural Networks

Artificial Neural Network is defined as an information management model that is identical to the function of biological nervous system of the human brain [17] which acts as an information processing machine. Thus, ANNs can handle complex non-linear time varyingreal-world problems [18] like man's brain which can compute a variety of complex signals.

ANN can be classified into Feed forward Neural Network (FFNN) and Recurrent Neural Network (RNN) [19]. Feed forward neural networks follow the principle of unidirectional information flow from input layer to output layer with no back-loops whereas recurrent neural networks do not have a restriction regarding back-loops.

### 2. Long Short-Term Memory

Long Short Term Memory (LSTM) is a type of recurrent neural network that finds its use in time series applications such as speech recognition, text recognition and language modeling [20] since it assimilates long-term dependencies. It is an appropriate method for prediction because it contains memory cell units to remember long time state values of sequential data, the gate units to learn the relevant state to retain and utilize [21]. It is preferable in the above-mentioned applications due to its ability to handle unstructured data and also structured data with a non-linear pattern. To the best of our knowledge, only a few attempts have been made using LSTM, especially in rainfall prediction. Hence an attempt is made in our research with a novel approach.

### 3. Methods For Prescriptive Analytics

Prescriptive analytics is an elevated level of analytics since it provides a suggestion for the predicted future state. It examines the forecast of possible outcomes from prediction where many choices and alternatives are provided that help to yield proactive decisions [22] as shown in Figure 1.3. Typically for any domain expert, it takes substantial time and effort to prescribe the best solution [23]. Hence to mitigate this, methodologies of prescriptive analytics become an essential part.

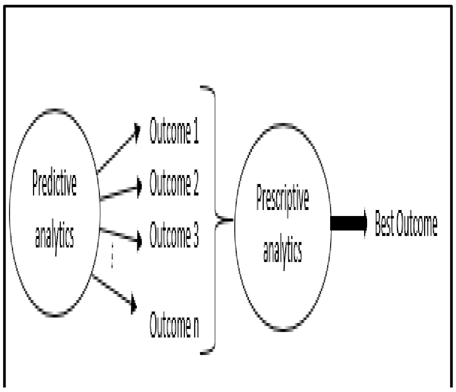


Figure 2 Role of prescriptive analytics.

Prescriptive analytics utilizes mathematical programming, evolutionary computation, simulation, logic-based models and sometimes probabilistic, machine learning methods [24]also for better decision making. Mathematical programming includes linear and non-linear optimization, stochastic optimization, fuzzy linear optimization and dynamic programming where as evolutionary computations are comprised of algorithms like genetic, greedy and particle swarm optimization. Fuzzy logic and clustering methods play a significant role inprecise decisions with non-numeric and numeric data, so we use these two methods.

### 4. Fuzzy Logic (Fl)

Fuzzy logic is a strategy to capture the approximate and inexact nature of the real world,similar to human thinking and natural language that deals with the ambiguity in mathematical logic [25]. It deals with the complex problems of human knowledge, represented by imprecise terms in the natural language by forming fuzzy sets and fuzzy rules [26]. Implementation of fuzzy logic is depicted in Figure 1. and it comprises of three steps [27] as follows,

- Fuzzification converts classical data into fuzzy data or Membership Function (MF).
- Fuzzy Inference Process integrates the membership functions with control rules to extract fuzzy output.
- Defuzzification creates a lookup table to obtain the output from the table for the given appropriate input.

A fuzzy set is an extension of a classical set whose elements have degrees ofmembership defined by a value between zero and one. The value one confirms theme mbership, zero the absence of membership and the values in-between a partial degree of membership [28]. Membership function determines the grade of membership of every element in the fuzzy set. The decision of appropriate action to be taken for the currentobserved information is illustrated by the fuzzy rule.

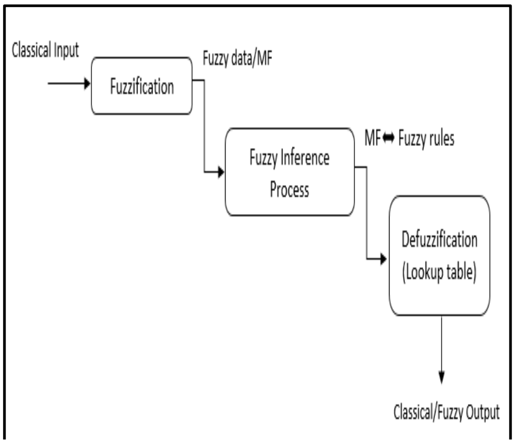


Figure 2 Steps involved in fuzzy logic.

**5.Clustering**

Clustering can be stated as an approach for unsupervised classification in machine learning that deals with defining classes for the given data without prior knowledge on class labels to identify a collection of similar objects based on a set of properties [29]. Clustering algorithms can be categorized under five groups [30],

- Partition based algorithms
- Hierarchical based algorithms
- Density based algorithms
- Grid based algorithms
- Model based algorithms

Hierarchical clustering algorithms manifest the relationship between each pair ofclusters formed in a stratified manner based on the measure of similarity or dissimilarity. Hierarchical clustering differs from partition based clustering in producing a nested seriesof partitions and not a single one [31]. Based on the algorithmic structure and operation, hierarchical clustering can be done in two ways,

- Agglomerative hierarchical clustering.
- Divisive hierarchical clustering.

Agglomerative hierarchical clustering is a bottom-up approach that initializes each feature in its cluster and repetitively unifies pairs of clusters that are closest until a single cluster remains as a root [32]. Divisive hierarchical clustering is a top-down approach that begins with all features as a single cluster and performs splitting until the stopping criteria are met [33].

## III. RESULTS&DISCUSSION

### 1. Challenges In Existing Methods For Rainfall Forecasting

From a broad survey on rainfall forecasting, it is clear that every model has its own merits and demerits but certain issues can be addressed by improving the model without losing the originality of the method. ARIMA is a standard statistical method used for most of the prediction applications that compete equally with machine learning models but due to its univariate forecasting nature, ANN overrides it. The following issues are yet observed in the existing methods.

- Traditional ANN uses a gradient descent algorithm for back propagation and hence suffers from vanishing gradient problem.
- It uses activation functions like sigmoid, tanh, etc., due to which the propagated error exponentially decreases due to their derivatives.
- It does not have the memory to hold the previous states of time series data.
- Convergence is slow to obtain the optimal values for network parameters.
- Suffers from the local minimum problem for longer forecasting periods, thus needing more number of epochs for better prediction. This increases computational complexity.
- Ensemble methods improvise the results but only to a certain level compared to the individual model.
- ANN produces good results for even less correlated input attributes but the system becomes unstable if more number of input parameters are used.
- Partial learning models may not generate the least error for all error measuring metrics.
- Prediction accuracy is good for any standard models like ARIMA, ANN during normal rainfall season but the accuracy goes down for the dry seasons.
- Minimum 30 years of data is needed to learn the weather pattern by the prediction models but most of the existing work (except a few) does not use a sufficient period for study.
- Classification algorithms give better results to find out rainfall occurrence but predicting the intensity of rainfall is difficult for even deep learning methods like LSTM.
- Quality of input data plays a vital role in deciding the accuracy of RNN.
- LSTM model with forget gate uses mostly Real-Time Recurrent Learning (RTRL) or TBPTT for weight update in which the network did not undergo learning with entire time series like BPTT.
- Deep learning models that use the BPTT method suffer from vanishing gradient.Some of the features in the rainfall forecast are considered as important which actsas the cause for the occurrence of above-listed challenges in the existing models.

Those features along with selected works from the literature survey are presented in Table 1 which gives an idea of the presence or absence of respective features in the models. It is necessary to find the intensity of rainfall for further processing like drought identification and water balance in the soil. Few works do not focus on it. Most of the methods could not support long-term forecasts due to the absence of BPTT, deep learning and the presence of vanishing or exploding gradients. However existing models thatperform deep learning rely on the number of layers but not deeper in time which mayinfluence the accuracy and error measure. These issues are addressed by the proposed model.

Table 1: Features of existing forecasting models.

| Methodology | Rainfall Intensity | Long-Term Forecast | BPTT | Vanishing/Exploding Gradient | Deep Learning (Layers/Time) |
|---|---|---|---|---|---|
| Svm | No | No | No | No | No |
| Bpnn | No | No | No | Yes | No |
| Mlp | Yes | No | No | Yes | No |
| Dbnpf | Yes | Yes | No | Yes | Layers |
| Deepesn | YES | NO | YES | YES | LAYERS |
| Lstm | Yes | No | Yes | Yes | Layers |

Methodology
Rainfall
Intensity
Long-Term
Forecast
BPTT
Vanishing/Exploding
Gradient Problem
Deep Learning
(Layers/Time)
SVM NO NO NO NO NO
BPNN NO NO NO YES NO
MLP YES NO NO YES NO
DBNPF YES YES NO YES LAYERS
Deep ESN YES NO YES YES LAYERS
LSTM YES NO YES YES LAYERS

## 2. Limitations In Data Analytics Using Machine Learning

Artificial intelligence and machine learning methods are preferred for data analytics nowadays for the reason of handling real-time data which is non-linear effectually. Machine learning models are built upon statistical framework, implemented as supervised and unsupervised algorithms. The following are the issues faced by machine learning models in general in trying to forecast the events, Time series issues: Unlike traditional prediction methods, time series forecasting adds on time component along with parameters used for forecasting. Hence the model must be able to incorporate the trend and seasonal pattern to the level component of every parameter correlated with forecasting. Most of the machine learning algorithms are developed based on classification problems but a different algorithmic approach is required for forecasting.Those models which perceive the ability to incorporate the foregoing states for predicting the succeeding outcomes are well suited for time series analysis. Recurrent neural networks are one among such models for handling time series forecasting.

**Lack of quality data-** Machine learning algorithms need sufficient data to train the model, for example at least 30 years of data for time series forecasting. The input must be in fixed time intervals and aligned [31] based on time. Missing values and erroneous training data will propagate the error into the forecasting variable. Also, data are expected to be a more granular level for better pattern learning whereas aggregation tends to favour macro-level learning. If the data pattern changes abruptly, there may be a high deviation in the forecast from the actual outcome.

**Accuracy concern-** Even though machine learning models are effective, they strive to attain the accuracy equivalent to statistical methods for forecasting. The reasoning behind is future errors, heterogeneous types of series, over-fitting in critical and inadmissible preprocessing [32]. Hence it is suggested to learn about unknown future errors by deseasonalizing the data, clustering the data into different categories of series, introducing the condition to break off the optimization process to avoid over-fitting and to opt necessary transformation and trend removal. Another major concern is that the model has to be trained for a change in data values every time and may not produce the same accuracy for test data.

**Lack of interpretability:-** Lack of transparency in internal logic and inner working of a model causes serious pitfalls as it prevents the experts to understand the reasoning and verify the decision made by the system [34]. Interpretability is the main inducement for the success of any artificial intelligence and machine learning system. Based on the degree of understanding why the decision was made by the system, a human can interpret the reason for prediction. Interpretability is also a cardinal reason for many researchers yet to adapt to statistical methods in various applications.

**Stochastic not deterministic:-**Many machine learning models focus on probability measures for prediction. So they do not follow any physical constraint like the acceptable values for the parameters used for forecasting. For example, rainfall value cannot be negative. So research focus on enumerating physical constraints in machine learning models will minimize the supplementary executions in prediction and integrate the predicted values for further analysis.Following the issues in machine learning for prediction, the limitations of prescriptive analytics are listed below. Integration with predictive analytics: Majority of the research work in data analytics concentrates on prediction and forecasting but fails to analyse the causes and effects on the outcomes.

Domain experts are approached for further decision making whereas it takes time for them to conduct a broad survey on the identical scenario and conclude on the same. Thus prescriptive analytics models ought to couple with prediction methods that will empower the decision-making system with appropriate reasoning for the conclusion made.

**Domain-specific model-** Principal motive of prescriptive analytics is to aid in decision making whereas it relies on precise domain and application. Conventional models available for data analytics are domain-general. They cannot be adapted as it is because every realtime application has distinct problems with contrasting parameters. Hence developing a domain-generic algorithm for prescriptive analytics is strenuous. So it has to hybridize the feasible algorithms with auspicious tuning which is also a challenging task to carry out successfully.

**Feedback mechanism is desired-** Prescriptive analytics maps the current situation to similar intervention in the past, along with the action performed previously [54]. So models that perceive the prior disposition are desired to be applicable for prescriptive analytics. The computational complexity and storage become a crucial issue in such recurrent algorithms that possess a feedback structure.

**Depend on human subjectivity-** Humans are adaptable to novel situations in nature but prescriptive analytics systems are not creative by themselves. The prescribed solution depends on the data and constraints set by the developer [54]. The intervention of humans is mandatory to verify the decision but the prescriptive analytics system can be trained to derive decisions based on appropriate reasoning that convinces the experts. To work out the reasoning for a certain decision prescribed, it consumes an enormous time for the experts to have a wide review of the problem in all aspects. Hence prescriptive analytics systems are in need to take over the part of analysis and reasoning.

## IV. CONCLUSIONS

Variability of weather in the present years leads to natural calamity either drought or flood depending upon the region. These cause loss of human life and properties. Additionally, it affects agriculture in several ways such as water scarcity, crop stress and crop failure. This decline in food production which in turn becomes a great challenge for the country to manage the supply of food grains to the people. Hence prediction of weather especially rainfall becomes mandatory to plan for water and farm management in agriculture. The precautions may be taken appropriately based on the upcoming scenario through the determination of flood and drought.

The existing rainfall prediction models such as statistical methods and ANNs are capable of forecasting certain weather features like temperature, humidity, wind speed, sunshine, etc., to a significant level. But these models are unable to predict highly non-linear data like rainfall for a longer period. The statistical methods rely on linear functions, ANNs do not have the memory to store the previous outputs, RNNs have short term memory and LSTM suffers from vanishing or exploding gradient problem on Back propagating to longer time steps that mitigate learning. Due to these reasons, the performance of existing models is insubstantial to forecast the rainfall.
To handle the above-mentioned issues efficiently, a time series forecasting model namely Intensified LSTM is proposed. It will enhance the learning of rainfall series and its predictor variables deeper in time thereby forecasting long-term rainfall for one year ahead.

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