Rainfall Prediction for Udaipur, Rajasthan Using Machine Learning Models Based on Temperature, Vapour Pressure and Relative Humidity

Jitendra Shreemali, Praveen Galav, Gaurav Kumawat, Pankaj Chittora

Abstract: The study aims at rainfall prediction using Machine Learning models using the minimum of features. The prediction here is based on temperature, vapour pressure and relative humidity. Numerous studies carried out earlier used more features than this study. A training-test split of 75-25 was used. The best results were obtained by combining the best of the candidate models into an ensemble model to identify that predictor importance of vapour pressure was 0.89 while that of relative humidity was 0.11 with temperature not seen as a significant predictor for rainfall though the high correlation of temperature (°C) with vapour pressure (Torr) and relative humidity (Percentage) suggests that the two predictor variables subsume the impact of temperature.

Keywords: Rainfall prediction, Neural Network, Ensemble model, CHAID, Random Forest

I. INTRODUCTION

Predicting weather patterns especially rainfall has been a challenge that mankind has grappled with since times immemorial. With agricultural production being directly or indirectly dependent on rainfall, it continues to draw immense interest among scientists as well as agriculturists across the globe. Rainfall also plays an important role in ensuring heat balance in the atmosphere on account of its direct impact on atmospheric circulation across the world. Katsaros and Buettner (1969) carried out an experimental study using a salt water tank to estimate impact of falling rain drops on salinity as well as temperature to understand how rain could affect oceans. They report that while smaller drops created a more stable surface, the larger ones led to increased mixing. Thus the impact of rainfall extends well beyond agriculture to multiple aspects of human existence.

Rainfall itself is the result of multiple and closely integrated natural processes that makes simulating the process model a very challenging task. However, the advancement of machine learning tools for predictive modeling preset an opportunity to fine tune the prediction accuracy but presents the challenge for researchers to identify appropriate model and relevant features that have a bearing on rainfall levels.

II. LITERATURE REVIEW

A comparison of different machine learning algorithms by Singh and Kumar (2019) finds that while adaptive boosting algorithm gave an F-score of 0.9726 on the test data while K-nearest, Neural Network and SVM gave F-scores of 0.8754, 0.7946, and 0.8045 respectively suggesting a superiority of adaptive boosting algorithm over the others listed here based on F-score without feature selection. Hong (2008) described using a hybrid model of RNN and SVM for forecasting rainfall depth values. The parameters of a SVR model (referred to as RSVR model) were chosen using the chaotic particle swarm optimization algorithm (CPSO). And applied to rainfall values during typhoon periods from Northern Taiwan. Their study provides a forecasting performance making the RSVRCPPO model an alternative worth considering for forecasting rainfall values. Based primarily on classification in terms of high-low-average Mohd, Butt and Baba (2018) considered the following parameters as candidate features for predicting rainfall: date, temperature in °C, Dew point in °C, Humidity as percentage, sea level pressure in hPa, visibility in KMs, wind speed in KM/h and precipitation in mm with the events of interest being the rainfall (snow, thunderstorm, fog) but used the average temperature, humidity, sea level pressure and wind speed to predict rainfall. They reported accuracy ranging from 82.56% to 87.76% and corresponding precision from 0.815 to 0.874. Janbandhu, Meshram and Gedam (2017) report using Bayesian Model to predict rainfall (mm) based on the following features: Temperature (°C), Station Level Pressure (hpa), Mean Sea Level Pressure (hpa), Relative humidity (percentage), Vapour Pressure (hpa) and Wind speed (Km/hour).

The results in use of monsoon season data across three cities, namely, Pune, Mumbai and Delhi are seen to be above 90% in all three cases. Swapna and Sudhakar (2018) report using the Long Short Term Memory (LSTM) deep Learning Model...
for rainfall prediction in coastal Andhra Pradesh with the features including Maximum as well as, Minimum temperature (both in °C), Wind, Pressure and Visibility. For inputs they used parameterized data inputs to predict rainfall. Using classification algorithms like SVM (Support Vector Machines), 2 layered ANN (Artificial Neural Networks) and logistic regression, Tarun et. al (2019) carried out qualitative analysis on data from the hydrological department of Rajasthan using 12 features and reported an accuracy of greater than 85% for the test data besides a precision value of 96% and recall of 91.4% for the logistic regression. Aftab et.al (2018) list the features used in different machine learning models aimed at predicting rainfall as including: polarity, quantity of rainfall, maximum and minimum temperature, humidity levels, wind speed etc. with the quality of prediction being a function of multiple factors including training algorithm, climatic attributes used as features and pre-processing techniques besides others. Oswal (2019) reported using a dataset with 23 features including location, minimum and maximum temperature, rainfall for the day in millimetres, evaporation, sunshine, wind gust direction, wind gust speed, wind direction at 9 AM and 3 PM, wind speed at 9 AM and 3 PM, humidity at 9 AM and 3 PM, atmospheric pressure at 9 AM and 3 PM, fraction of sky obscured by clouds at 9 AM and 3 PM and precipitation. While a large number of features does increase the chances of greater accuracy, it inevitably increases data collection and computation costs. To predict rainfall through reduced features thereby reducing data collection costs and computation efforts was the primary motivating factor behind this study.

Udaipur, a city also referred to as the City of Lakes is a popular tourist spot for people all over the world. The city was founded in 1558 by Maharana Udai Singh at a very scenic spot on the south slope of Aravalli Ranges in Rajasthan, India. Wikipedia quotes James Tod on Udaipur being “…the most romantic spot on the Continent of India”. It’s natural beauty and attractiveness for tourists depends almost entirely on the rainfall in the area. Udaipur’s weather in terms of temperature and rainfall are given below:

Rainfall data for Udaipur is summarized below:

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III. DATA COLLECTION AND PREPARATION

Data on rainfall and temperature was collected from government site for data (https://data.gov.in) while data for Relative Humidity and Vapour Pressure was collected from the NASA site (https://search.earthdata.nasa.gov). Temperature, relative humidity and vapour pressure during the month from 1983 to 1990 were used as features to predict monthly rainfall. Since all possible values were not available available, average values were treated as estimator for Temperature, relative humidity and vapour pressure during the month bringing an element of error into the system because these values are not consistent during the entire month.

Table 1: Weather Data Elements

<table>
<thead>
<tr>
<th>Sl.No.</th>
<th>Attribute</th>
<th>Data Type</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Temperature</td>
<td>Continuous</td>
<td>°C</td>
</tr>
<tr>
<td>2</td>
<td>Vapour Pressure</td>
<td>Continuous</td>
<td>Torr</td>
</tr>
<tr>
<td>3</td>
<td>Relative Humidity</td>
<td>Continuous</td>
<td>Percent</td>
</tr>
<tr>
<td>4</td>
<td>Rainfall (Target variable)</td>
<td>Continuous</td>
<td>MM</td>
</tr>
</tbody>
</table>

IV. MODEL TRAINING AND EVALUATION

IBM SPSS Modeler was used to build and train the models. Given the fact that all variables are continuous in nature, following twelve models were considered for model building. These are: (i) Regression; (ii) Generalized regression; (iii) Linear-AS; (iv) LSVM; (v) Random Trees; (vi) Tree-AS; (vii) XGBoost Linear; (viii) XGBoost Tree; (ix) Linear; (x) CHAID; (xi) Random Forest; (xii) Neural Net. A Partitioning of 75% for training and 25% for testing was used. A representation of these is presented below:
Multiple models were attempted to improve the accuracy.

V. RESULTS AND DISCUSSIONS

Use of multiple machine learning algorithm increases the chances of getting better results when no single algorithm is seen to produce optimal results under all conditions. In this specific case, the following six models producing the best results (in descending order): (i) Linear; (ii) Neural Net; (iii) Regression; (iv) Generalized Linear; (v) CHAID; and (vi) Random Forest. The result reported relate to the ensemble model that helps address limitations of individual models and also enhances accuracy. These results are presented below as Figure 3:

![Figure 2: Schematic of Various Models Built](image1)

Figure 2: Schematic of Various Models Built

Considering the variation in results across different machine learning models, the results of each model in terms of error, standard deviation and correlation (eg. linear correlation values falling between 0.909 to 0.636) are presented below:

![Figure 3: Summary of ML Models](image2)

Figure 3: Summary of ML Models

Regression Models: The Linear (regression) model for machine learning is built around the equation:

\[ Y_{\text{Pred}} = B_0 + B_1 \times X_1 \]

with \( B_0 \) signifying the intercept (bias) and \( B_1 \) signifying the slope (weight) of the parameter. Depending upon the number of features the prediction can be a line, a plane or a hyperplane. Machine learning uses different kinds of regression models where the key difference lies in the underlying equation, how parameters are learnt during training and how model complexity is kept under control to avoid overfitting.

Generalized linear (regression) models extend the simple method above to cater to added complexity brought in by multiple impacting variables. This equation takes the general form:

\[ Y_{\text{Pred}} = b_0 + b_1 \times X_1 + b_2 \times X_2 + b_3 \times X_3 + \ldots \]

with the model estimating all \( b_i \)'s.

Where linearity does not hold, models would go in for non-linear functions (eg. the sigmoid function).

Neural Net: Neural networks are algorithms modeled around the human brain with the nodes representing neurons and layers in the network representing clustering, classification or regression algorithms to manage the data fed at the input layer.

![Figure 4: Ensemble Model Results](image3)

Figure 4: Ensemble Model Results

![Figure 5: Neural Network Results](image4)

Figure 5: Neural Network Results

![Figure 6: Random Trees Results](image5)

Figure 6: Random Trees Results

![Figure 7: Random Forest Model Results](image6)

Figure 7: Random Forest Model Results

Given below is a very brief description of these models listed above:

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with \( b_0 \) signifying the intercept (bias) and \( b_1 \) signifying the slope (weight) of the parameter. Depending upon the number of features the prediction can be a line, a plane or a hyperplane. Machine learning uses different kinds of regression models where the key difference lies in the underlying equation, how parameters are learnt during training and how model complexity is kept under control to avoid overfitting.

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Since one layer as well as linearity are often insufficient excepting for the simplest of purposes, multiple layers and non linear activation functions are needed for accurate prediction, classification or clustering making multiple layers (i.e. deep learning) a necessity that can not be done away with.

Neural networks, like different regression models aim at estimating the weight parameters to minimize the error (or loss/cost). Starting with the artificial neural networks, the subsequent developments of convolutional neural networks and recurrent neural networks at doing this for while also optimizing computation load and improving accuracy of prediction, clustering or classification as the case be.

CHAID Model: Chi-Squared Automatic Interaction Detector model is an evolution of earlier AID and THAID (Theta AID) models. The analysis aims at building a predictive model and helps develop an understanding of how variables best merge to help estimate a given dependent variable. The popularity of CHAID model lies partly in its ability to allow use of nominal, ordinal as well as continuous data. CHAID creates multiple cross tabulations for each categorical predictor to arrive at the best outcome. A systematic approach is adopted to build the decision tree starting with the dependent variable forming the root node. The constituents of this root node are split into two or more categories based on mathematical indices to arrive at the best ordered distribution that explains the relationships between variables with the highest accuracy even though these variables may not necessarily be normally distributed.

Random Forest: Random Forest is a supervised learning algorithm used more for the purpose of classification though it can well be used for regression too. The algorithm utilizes a voting mechanism among the largest possible (decision) trees built from data samples to arrive at the best solution for predicting the outcome. The large number of relatively uncorrelated trees arriving at the prediction through a voting mechanism greatly enhances the accuracy while also reducing chances of over-fitting.

Based on the analysis carried out and using the feature of IBM SPSS Modeler that combines the best of candidate models into a single ensemble model with the best results (accuracy) shows that Vapour Pressure and Relative humidity are the key parameters for predicting rainfall with a relative importance of 0.89 and 0.11 with Temperature not being a statistically significant factor as shown in the Figure 6 below.

The low importance of temperature could be due to a high correlation between the variables as seen by the correlation matrix below:

\[
\begin{array}{ccc}
\text{Temp} & \text{Vap. Pr.} & \text{Rel.Hum} \\
\text{Temp} & 1 & 0.648847 \\
\text{Vap. Pr.} & 0.648847 & 1 \\
\text{Rel.Hum} & 0.726633 & 0.515658 & 1 \\
\end{array}
\]

To visually examine the quality of prediction, a plot of predicted (on X-Axis) versus actual rainfall (on Y Axis) is shown in Figure 7 below:
The graphical representation indicates greater spread (error) in the middle as compared to the extremities.

Auditor Report for the Model is shown in Figure 13 below:

<table>
<thead>
<tr>
<th>Field</th>
<th>Graph</th>
<th>Measurement</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall</td>
<td>Continuous</td>
<td>4.000</td>
<td>186.00</td>
<td>49.755</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temp_C</td>
<td>Continuous</td>
<td>16.818</td>
<td>33.325</td>
<td>25.619</td>
<td>0.214</td>
<td></td>
</tr>
<tr>
<td>U_P_Torr</td>
<td>Continuous</td>
<td>6.334</td>
<td>29.661</td>
<td>16.128</td>
<td>0.661</td>
<td></td>
</tr>
<tr>
<td>Real_Hum</td>
<td>Continuous</td>
<td>12.010</td>
<td>85.833</td>
<td>43.669</td>
<td>0.178</td>
<td></td>
</tr>
<tr>
<td>Partllion</td>
<td>Nominal</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>DRR_Rainfall</td>
<td>Continuous</td>
<td>-26.023</td>
<td>225.109</td>
<td>109.802</td>
<td>0.834</td>
<td></td>
</tr>
<tr>
<td>SRE_Rainfall</td>
<td>Continuous</td>
<td>0.925</td>
<td>26.782</td>
<td>9.100</td>
<td>0.525</td>
<td></td>
</tr>
</tbody>
</table>

VI. LIMITATIONS OF THE STUDY AND SCOPE FOR FURTHER STUDY

The key limitation of the study stems from the use of average values of the features (temperature, vapour pressure and relative humidity) for a given month. Since there can be significant variation over a month, the accuracy of estimation is expected to increase significantly if the model granularity is improved so that the time intervals considered are smaller, say, a period of a few days. Also the relatively small dataset suggests the need for a deeper study.

VII. CONCLUSION

The study suggests that machine leaning techniques make it possible to predict rainfall based on vapour pressure, relative humidity and temperature. This opens the possibility of significant variable reduction for predicting rainfall but care must be exercised since the duration of data was less than a decade. Applying the model over an extended period in multiple geographic locations would be required to add to its reliability.

REFERENCES


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Prof (Dr.) Jitendra Shreemani is a graduate from IIT Madras with post graduate from IIM Bangalore. He is working as Professor of the Department of Computer Science and Engineering at Techno India NJR Institute of Technology Udaipur. He has worked in reputed companies in India & abroad for about a decade and half followed by about two decades of academic/ research/ training experience. He has taught a very wide variety of courses including operations management, research methodology, and data science besides others. His areas of work include data science, optimization, mathematical modeling and machine learning.
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