A technique for spot weather forecasting

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(Received 20 June 2013, Modified 11 September 2013)

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ABSTRACT. The emphasis of present work is to provide some guidance to the operational forecasters for indicating the possible occurrence of rainfall (wet day) before 24 hours and 48 hours during Northeast and Southwest monsoon season over the inland station Trichirappalli (Latitude 10° 46' N / Longitude 78°43' E) of south India. The interesting aspect of the methodology is that it is based only on the "in situ" data of meteorological parameters. Data mining technique is used. The weather patterns of hot day and cold day for April and May months during summer and January, February and March months during winter respectively have also been extracted using the same method. The study shows that the proposed data mining model can predict the occurrence of rainfall, hot day during summer and cold day during winter with the help of local weather parameters.

Key words – Association rule, Data mining, Weather pattern, Weather forecasting.

1. Introduction

Weather forecast is mostly for a region based on synoptic situations. The forecast model may be either synoptic or numerical one (Balachandran et al., 2006; Dhar and Rakhecha, 1983; Kripalani and Kumar, 2004; Kumar et al., 2007; Mohanty et al., 2001; Nayagam Lorna, 2009; Raj, 1996; Rao, 1963; Shukla and Mooley, 1987; Sivaramakrishnan and Sreedharan 1988,1989; Sridaran and Muthuchami, 1990; Zubair and Ropelewski, 2006). The models need the input of meteorological parameters at different grid points. During the passage of clean tropical systems, sequence of events is known and mostly the knowledge of the sequence is helpful for predicting the weather. Cyclones and summer monsoon activity (Mukherjee and Sivaramakrishnan, 1977; Rao, 1976; Raghavan et al., 1983; Sivaramakrishnan and Prasad, 1999) are the few systems with clear cut rainfall patterns over any place. A few investigations on the nature and trend of point rainfall as well as its prediction (Seetharam, 2009; Sivaramakrishnan, 1988) are also seen. However need for forecast at specific location is increasing day by day. Industrial townships, space stations, harbours etc. need this. Again metropolitan cities also seek such spot forecast for national festivals, sports and similar occasions.

Operationally point rainfall (RF) forecast is given to a very limited extent. Nevertheless radar and satellite data of the recent decades help in assessing the rain potential of clouds (Raghavan et al., 1987). However this type of rain forecast is effective for 12 hours or less. A useful forecast has to be at least 24 hours ahead. If it is 48 hours ahead that is preferable for operational exercise. Recently the authors have successfully developed some methods to forecast wet and dry days based on data mining techniques for some coastal stations of east coast of India (Meganathan et al., 2009; Sivaramakrishnan and Meganathan 2011, 2012a, 2012b, 2012c, 2013). In the present paper, a similar model is tried for a sample inland station, Trichirappalli of south India.
TABLE 1
Nominal values for atmospheric parameters

| Weather parameter | Nominal variable | Nominal values |
|-------------------|-----------------|----------------|
|                   |                 | 24 hr NE | 48 hr NE | 24 hr SW | 48 hr SW |
| Temperature       | T_L             | < 75.13  | < 75.56  | < 81.66  | < 81.93  |
|                   | T_M             | 75.13 - 82.46 | 75.56 - 83.16 | 81.66 - 88.83 | 81.93 - 89.36 |
|                   | T_H             | > 82.46  | > 83.16  | > 88.83  | > 89.36  |
| Dew Point         | D_L             | < 60     | < 60     | < 63.03  | < 63.03  |
|                   | D_M             | 60 - 68.9 | 60 - 68.9 | 63.03 - 70.86 | 63.03 - 70.86 |
|                   | D_H             | > 68.9   | > 68.9   | > 70.86  | > 70.86  |
| Wind Speed        | W_L             | < 8.53   | < 8.53   | < 10.53  | < 10.53  |
|                   | W_H             | > 17.06  | > 17.06  | > 20.76  | > 20.76  |
| Visibility        | V_L             | < 5.13   | < 5.13   | < 5.2    | < 5.2    |
|                   | V_M             | 5.13 - 9.86 | 5.13 - 9.86 | 5.2 - 8.6 | 5.2 - 8.6 |
|                   | V_H             | > 9.86   | > 9.86   | > 8.6    | > 8.6    |
| Precipitation     | YES             | > 0      | > 0      | > 0      | > 0      |
|                   | NO              | = 0      | = 0      | = 0      | = 0      |

2. Data used

Trichirappalli (Latitude 10°46’ N / Longitude 78° 43’ E) is located in Tamil Nadu state of South India which is a metropolitan area with an airport. India Meteorological Department (IMD) has a full fledged observatory here. Rainy days during southwest (SW) monsoon and northeast (NE) monsoon as well as minimum temperature during winter and maximum temperature during summer have been taken as the parameters for the forecast because of their operational importance. Data used are those recorded by IMD and then included in World Meteorological Organization (WMO) data bank as managed by the National Oceanic and Atmospheric Administration (NOAA), which is a federal agency focused on the condition of the oceans and the atmosphere worldwide. Daily rainfall data for the years 1961-2010 were considered for developing the model.

Our data set consists of five atmospheric variables including temperature, dew point, wind speed, visibility and precipitation (rainfall). The data set that we extracted consists of the prevailing atmospheric situations 24 hours and 48 hours before the actual occurrence of the rain during the North East monsoon months of October, November and December as well as the South West monsoon months of June, July, August and September. Data preprocessing steps were applied on the raw set of seasonal data and they were converted to nominal values by applying filtering using unsupervised attribute of discretization algorithm. After the filtering operations were carried out, a total of 3393 instances for 24 hours advance wet day prediction in NE monsoon, a total of 3398 instances for 48 hours advance wet day prediction and 4609 and 4614 instances respectively for 24 hours advance prediction and 48 hours advance prediction during SW monsoon were present for analysis. The discretization algorithm produced various best-fit ranges for the five atmospheric conditions we used in analysis. Based on the discretization algorithm the atmospheric variables are ranged into the nominal values low, medium and high with its best ranges using machine learning tool Weka 3.6. The nominal values for the atmospheric parameters are shown in Table 1.

3. Methodology

3.1. Association rule mining for prediction

The problem of mining association rule was first introduced in the last decade by database communities (Agrawal and Srikant, 1994; Agrawal et al., 1995). Association rule mining aims to extract the interesting correlations, associations, frequent patterns among set of weather items in climate data repository. For the spot specific forecast, the derived frequent weather patterns are
TABLE 2
Generated association rules for 24 hours ahead rainfall prediction during SW monsoon with support and confidence values

| Association Rule \( (A \Rightarrow B) \) | \( \text{Support} \ (A \cup B) \) | \( \text{Confidence} \ P(B/A) \) |
|------------------------------------------|----------------------|------------------|
| TEMP = \( (-\infty - 81.666667) \) DEWP = \( (70.866667-\infty) \) VISIB = \( (5.2-8.6) \) | 18 | 0.77891 |
| WDSP = \( (-\infty - 10.53333) \) \Rightarrow PRCP = yes | | |
| TEMP = \( (-\infty - 81.666667) \) DEWP = \( (63.033333-70.866667) \) VISIB = \( (\infty - 5.2) \) | 20 | 0.75277 |
| WDSP = \( (5.2-8.6) \) \Rightarrow PRCP = no | | |
| TEMP = \( (88.833333-\infty) \) DEWP = \( (63.033333-70.866667) \) VISIB = \( (\infty - 5.2) \) | 161 | 0.93478 |
| WDSP = \( (-\infty - 10.53333) \) \Rightarrow PRCP = no | | |
| TEMP = \( (88.833333-\infty) \) DEWP = \( (70.866667-\infty) \) WDSP = \( (\infty - 10.53333) \) \Rightarrow PRCP = no | 124 | 0.98943 |
| TEMP = \( (81.666667-88.833333) \) WDSP = \( (20.766667-\infty) \) \Rightarrow PRCP = no | | |
| TEMP = \( (88.833333-\infty) \) DEWP = \( (63.033333-70.866667) \) WDSP = \( (\infty - 10.53333) \) \Rightarrow PRCP = no | 108 | 0.9087 |
| DEWP = \( (\infty - 10.53333) \) VISIB = \( (8.6-\infty) \) WDSP = \( (\infty - 10.53333) \) \Rightarrow PRCP = yes | 164 | 0.87631 |
| TEMP = \( (88.833333-\infty) \) VISIB = \( (\infty - 5.2) \) WDSP = \( (\infty - 10.53333) \) \Rightarrow PRCP = yes | 25 | 0.65351 |

represented in the form of association rules. These information leads to the discovery of interesting associations and correlations within the data with the help of support and confidence measures for the occurrence of the weather event. Recently the authors (Sivaramakrishnan and Meganathan, 2013) have reported the suitability of association rule approach for point rainfall prediction 24 hours ahead in a case study. When we apply the above association rule concept to studying meteorological data, with each record listing various atmospheric observations including wind direction, wind speed, temperature, relative humidity, rainfall and mean sea level pressure taken at a certain time in certain area we can find association rules like,

\( R_1 \): If the humidity is medium wet, then there is no rain in the same area at the same time.

Although rule \( R_1 \) reflects some relationships among the meteorological elements, its role in weather prediction is inadequate. The association rule has been used in climatology applications with more number of parameters. The following rule emphasis the occurrence of the weather event with available atmospheric conditions.

\( R_2 \): If the wind direction is east and the weather is warm, then it keeps warm for the next 48 hour.

\( R_3 \): If temperature is low, dew point is high, wind speed is medium then precipitation has occurred.

For example, a derived weather pattern for the wet day prediction, Temp is “\( T_{LOW} \)” and Dew point is “\( D_{HIGH} \)” and Visibility is “\( V_{MEDIUM} \)” and Wind speed is “\( W_{LOW} \)” that emphasis the occurrence of the wet day. The temperature, dew point, visibility, wind speed and wind speed are the input atmosphere parameters. If the values for these variables would be within their nominal value range as shown in Table 1, which is fixed by the machine learning tool, then precipitation will be occurred. The class label “precipitation” describes it. We used predictive Apriori algorithm for deriving the association rule from the preprocessed dataset. The basic property of Apriori is that the non-empty subsets of a frequent item set must be frequent. In connection with the above the predictive Apriori algorithm searches with an increasing support threshold for the best ‘n’ rules concerning a support-based corrected confidence value.

Predictive mining is a task that it performs inference on the current data in order to make a prediction. Here the climate parameters temperature, dew point, visibility, wind speed and precipitation are taken for analysis using classification and association mining. The rule \( A \Rightarrow B \) holds in the transaction set \( D \) with support \( s \), where \( s \) is the percentage of transactions in \( D \) that contain \( A \cup B \) (i.e., the union of sets A and B, or say, both A and B). This is taken to be the probability, \( P(A \cup B) \). The rule \( A \Rightarrow B \) has confidence \( c \) in the transaction set \( D \), where, \( c \) is the percentage of transactions in \( D \) containing A that
TABLE 3
Generated association rules for 48 hours ahead rainfall prediction during SW monsoon with support and confidence values

| Association Rule \( A \Rightarrow B \) | Support \( \left( A \cup B \right) \) | Confidence \( P(B|A) \) |
|----------------------------------------|----------------|----------------|
| \( \text{TEMP} = '(89.366667-\text{inf})' \ \text{DEWP} = '(63.033333-70.866667) \) \text{VISIB} = '(-\text{inf}-5.2]' \ \text{WDSP} = '(10.533333-20.766667) \) \Rightarrow \text{PRCP} = \text{no} | 261 | 0.88738 |
| \( \text{TEMP} = '(-\text{inf}-81.933333\)) \ \text{DEWP} = '(63.033333-70.866667) \) \text{WDSP} = '(10.533333-20.766667) \) \Rightarrow \text{PRCP} = \text{no} | 12 | 0.86619 |
| \( \text{TEMP} = '(89.366667-\text{inf})' \ \text{DEWP} = '(70.866667-\text{inf})' \ \text{WDSP} = '(10.533333-20.766667) \) \Rightarrow \text{PRCP} = \text{no} | 122 | 0.83411 |
| \( \text{TEMP} = '(81.933333-89.366667) \) \ \text{DEWP} = '(63.033333-70.866667) \) \text{WDSP} = '(10.533333-20.766667) \) \Rightarrow \text{PRCP} = \text{no} | 1402 | 0.65042 |
| \( \text{TEMP} = '(81.933333-89.366667) \) \ \text{DEWP} = '(63.033333-70.866667) \) \ \text{VISIB} = '(5.2-8.6]' \ \Rightarrow \text{PRCP} = \text{yes} | 11 | 0.4998 |
| \( \text{TEMP} = '(-\text{inf}-81.933333\)) \ \text{DEWP} = '(70.866667-\text{inf}) \) \ \text{VISIB} = '(8.533333-17.066667\) \ \text{PRCP} = \text{yes} | 20 | 0.4762 |

TABLE 4
Generated association rules for 24 hours ahead rainfall prediction during NE monsoon with support and confidence values

| Association Rule \( A \Rightarrow B \) | Support \( \left( A \cup B \right) \) | Confidence \( P(B|A) \) |
|----------------------------------------|----------------|----------------|
| \( \text{TEMP} = '(75.133333-82.466667) \) \ \text{DEWP} = '(60-68.9)' \ \text{VISIB} = '(5.133333-9.866667) \) \ \text{WIND} = '(-\text{inf}-8.533333) \) \Rightarrow \text{PRCP} = \text{yes} | 31 | 0.99155 |
| \( \text{TEMP} = '(82.466667-\text{inf})' \ \text{DEWP} = '(60-68.9)' \ \text{VISIB} = '(-\text{inf}-5.133333) \) \ \text{WIND} = '(8.533333-17.066667)' \ \Rightarrow \text{PRCP} = \text{yes} | 24 | 0.94504 |
| \( \text{TEMP} = '(-\text{inf}-75.133333\)) \ \text{DEWP} = '(-\text{inf}-68.9) \) \ \text{WIND} = '(-\text{inf}-5.133333) \) \ \text{WIND} = '(8.533333-17.066667)' \ \Rightarrow \text{PRCP} = \text{no} | 34 | 0.8335 |
| \( \text{TEMP} = '(-\text{inf}-75.133333\)) \ \text{WIND} = '(17.066667-\text{inf})' \ \Rightarrow \text{PRCP} = \text{no} | 3 | 0.89357 |
| \( \text{TEMP} = '(-\text{inf}-75.133333\)) \ \text{WIND} = '(-\text{inf}-68.9) \) \ \text{WIND} = '(8.533333-17.066667)' \ \Rightarrow \text{PRCP} = \text{no} | 34 | 0.8335 |

also contain B. This is taken to be the conditional probability, \( P(B|A) \). That is,

\[
\text{Support} \left( A \Rightarrow B \right) = P \left( A \cup B \right)
\]

\[
\text{Confidence} \left( A \Rightarrow B \right) = \frac{\text{Support}_\text{count} \left( A \cup B \right)}{\text{Support}_\text{count} \left( A \right)}
\]

Recently association rule mining was successfully verified for prediction of rainfall just 24 hours before (Sivaramakrishnan and Meganathan, 2011). The predictive Apriori algorithm shows the best association rules. Some of the best rules that have been predicted from the given dataset are shown in Table 2 for 24 hour advance rainfall prediction during SW monsoon, Table 3 for 48 hour advance rainfall prediction during SW monsoon and Table 4 for 24 hour advance rainfall prediction during NE monsoon. Each and every association rule consists with a support and confidence value that determines the credibility of the rule.

3.2. Classification

Classification is a learning function that maps the data into one of the several predefined data classes. It is a
TABLE 5
Statistical summary of rainfall prediction on SW and NE monsoon

| Measures                        | Southwest monsoon | Northeast monsoon |
|---------------------------------|-------------------|-------------------|
|                                 | 24 hour before    | 48 hour before    | 24 hour before    | 48 hour before    |
| Total number of instances       | 4609              | 4614              | 3393              | 3394              |
| Correctly classified instances  | 3712              | 3698              | 2254              | 2189              |
| Incorrectly classified instances| 897               | 916               | 1139              | 1205              |
| Correctly classified in %       | 80.5381           | 80.1474           | 66.43             | 64.5              |
| Incorrectly classified in %     | 19.4619           | 19.8526           | 33.57             | 35.5              |
| Mean absolute error             | 0.2759            | 0.2948            | 0.4197            | 0.4673            |
| Root mean squared error         | 0.367             | 0.3818            | 0.4197            | 0.4807            |

TABLE 6
A confusion matrix for positive and negative tuples of precipitation prediction

| Actual class | Predicted class | Precipitation = YES | Precipitation = NO |
|--------------|-----------------|--------------------|-------------------|
| Precipitation = YES | True positives | False negatives |
| Precipitation = NO       | False positives | True negatives |

TABLE 7
Confusion matrix for wet/dry day prediction on SW and NE monsoon

| Monsoon | Prediction type | True positives | False negatives | False positives | True negatives | No. of instances | Correlation coefficient |
|---------|-----------------|----------------|-----------------|-----------------|----------------|------------------|------------------------|
|         | 24 hr advance   | 81             | 833             | 64              | 3631           | 4609             | 80.5 %                 |
|         | 48 hr advance   | 0              | 916             | 0               | 3698           | 4614             | 80.1 %                 |
| Northeast| 24 hr advance   | 2175           | 18              | 1121            | 79             | 3393             | 66.4 %                 |
|         | 48 hr advance   |                |                 |                 |                | 3394             | 64.5 %                 |

form of data analysis that can be used to extract models describing important class to predict future data trends. It predicts on categorical labels like occurrence of wet day, occurrence of cool day, occurrence of hot day etc. Classification is used to predict the data classes whose class label is unknown. Here we use K* classification algorithm (Cleary and Trigg, 1995) which is an instance based classifier, that is the class of a test instance is based upon the class of those training instances similar to it, as determined by some similarity function, such as entropy based similarity function. By using this, the discretized data of the atmospheric situations before 24 hours and 48 hours of the actual rainy day was evaluated and the coherence of correctly classified instances and incorrectly classified instances were found out to justify the accuracy of the data prediction model we used.

In this paper the data class “PRCP” is used for wet and dry day forecasting during SW and NE monsoon season of sample station that has two values “yes” and “no”. The value “yes” in the derived pattern of the association rule describes the occurrence of the wet day. The value “no” in the derived pattern of the association rule describes the occurrence of the dry day. Similarly the forecasting of the cool day during winter months, the derived pattern of the association rule has the class label “POST_MIN” which has two values “nor” and “low”. The class label value “nor” is meant for the normal winter day
and “low” is for the extreme winter day (i.e., cool day). The class label “POST_MAX” is for the hot day prediction during summer months whose values are “nor” and “high” which describe normal summer day and extreme summer day (i.e., hot day) respectively.

4. Results and discussion

4.1. Validation

Validation for our model has been done using the 10-fold cross validation, percentage split method and supplied test method. The basic notions of those methods have been described here. Classifiers rely on being trained before they can reliably be used on new data. Of course, it stands to reason that the more instances the classifier is exposed to during the training phase, the more reliable it will be as it has more experience. However, once trained, we would like to test the classifier too, so that we are confident that it works successfully. For this, yet more unseen instances are required.

A problem that often occurs is the lack of readily available training/test data. These instances must be pre-classified which is typically time-consuming. A method to circumvent this issue is known as cross-validation. It works as follows:

(i) Separate data in to fixed number of partitions (or folds).

(ii) Select the first fold for testing, whilst the remaining folds are used for training.

### TABLE 8

| Prediction type         | No. of samples | Correlation coefficient | Class  | TP rate  | FP rate  | Precision | Recall  | F-measure | ROC area |
|-------------------------|----------------|-------------------------|--------|----------|----------|-----------|---------|-----------|----------|
| 24 hour advance in NE monsoon | 3393            | 66.4309                  | NO     | 0.666    | 0.008    | 0.814     | 0.066   | 0.122     | 0.689    |
|                         |                |                         | YES    | 0.992    | 0.934    | 0.66      | 0.099   | 0.792     | 0.689    |
|                         |                |                         | Wg. Avg| 0.664    | 0.607    | 0.715     | 0.664   | 0.555     | 0.689    |
| 48 hour advance in NE monsoon | 3394            | 64.4909                  | NO     | 0.617    | 0.316    | 0.717     | 0.617   | 0.663     | 0.669    |
|                         |                |                         | YES    | 0.684    | 0.383    | 0.579     | 0.684   | 0.627     | 0.669    |
|                         |                |                         | Wg. Avg| 0.646    | 0.345    | 0.657     | 0.646   | 0.648     | 0.669    |
| 24 hour advance in SW monsoon | 4609            | 80.5381                  | NO     | 0.983    | 0.911    | 0.813     | 0.983   | 0.89      | 0.758    |
|                         |                |                         | YES    | 0.089    | 0.017    | 0.559     | 0.089   | 0.153     | 0.758    |
|                         |                |                         | Wg. Avg| 0.805    | 0.734    | 0.763     | 0.805   | 0.744     | 0.758    |
| 48 hour advance in SW monsoon | 4609            | 80.1474                  | NO     | 1        | 1        | 0.801     | 1       | 0.89      | 0.695    |
|                         |                |                         | YES    | 0        | 0        | 0         | 0       | 0         | 0.695    |
|                         |                |                         | Wg. Avg| 0.801    | 0.801    | 0.642     | 0.801   | 0.713     | 0.695    |

### TABLE 9

| Monsoon  | Prediction type | No. of samples | Correlation coefficient (%) | Testing years (%) |
|----------|-----------------|----------------|-----------------------------|-------------------|
| Southwest| 24 hr prior     | 4609           | 80.5381                     | 76 68 80 85 66    |
|          | 48 hr prior     | 4609           | 79.5411                     | 77 68 80 85 64    |
| Northeast| 24 hr prior     | 3393           | 66.4                        | 56 69 73 63 47    |
|          | 48 hr prior     | 3394           | 64.5                        | 56 69 63 43 59    |
### TABLE 10
Generated association rules for 24 hours before cold day prediction during winter months with support and confidence values

| Association Rule \( A \Rightarrow B \) | Support \( A \cup B \) | Confidence \( P(B/A) \) |
|----------------------------------------|-----------------|-----------------|
| MAX = '⟨82.8-91.8⟩' MIN = '⟨60.2-70.4⟩' DEWP = '⟨-inf-58.86667⟩' VISIB = '⟨-inf-4.7⟩' \( \Rightarrow \) POST_MIN = low | 15 | 0.98572 |
| MAX = '⟨91.8-inf⟩' WDSP = '⟨9.533333-18.266667⟩' \( \Rightarrow \) POST_MIN = nor | 14 | 0.98487 |
| MIN = '⟨70.4-inf⟩' DEWP = '⟨67.733333-18.266667⟩' WDSP = '⟨9.533333-18.266667⟩' \( \Rightarrow \) POST_MIN = nor 131 | 134 | 0.97931 |
| MAX = '⟨-inf-82.8⟩' DEWP = '⟨67.733333-18.266667⟩' VISIB = '⟨-inf-4.7⟩' \( \Rightarrow \) POST_MIN = nor 75 | 77 | 0.97789 |
| MAX = '⟨82.8-91.8⟩' DEWP = '⟨-inf-58.86667⟩' VISIB = '⟨-inf-4.7⟩' \( \Rightarrow \) POST_MIN = low 16 | 17 | 0.94013 |
| MAX = '⟨82.8-91.8⟩' MIN = '⟨60.2-70.4⟩' DEWP = '⟨-inf-58.86667⟩' WDSP = '⟨-inf-9.533333⟩' \( \Rightarrow \) POST_MIN = low 14 | 15 | 0.92932 |

### TABLE 11
Generated association rules for 48 hours before cold day prediction during winter months with support and confidence values

| Association Rule \( A \Rightarrow B \) | Support \( A \cup B \) | Confidence \( P(B/A) \) |
|----------------------------------------|-----------------|-----------------|
| MAX = '⟨91.8-inf⟩' MIN = '⟨70.4-inf⟩' WDSP = '⟨-inf-9.533333⟩' \( \Rightarrow \) POST_MIN = nor | 206 | 0.99497 |
| MAX = '⟨91.8-inf⟩' DEWP = '⟨67.733333-18.266667⟩' WDSP = '⟨-inf-9.533333⟩' \( \Rightarrow \) POST_MIN = nor | 174 | 0.99494 |
| MAX = '⟨82.8-91.8⟩' MIN = '⟨70.4-inf⟩' VISIB = '⟨-inf-5.566667⟩' WDSP = '⟨9.533333-18.266667⟩' \( \Rightarrow \) POST_MIN = nor | 150 | 0.95884 |
| MAX = '⟨82.8-91.8⟩' MIN = '⟨60.2-70.4⟩' DEWP = '⟨-inf-58.86667⟩' WDSP = '⟨-inf-9.533333⟩' \( \Rightarrow \) POST_MIN = low | 15 | 0.78154 |
| MAX = '⟨82.8-91.8⟩' DEWP = '⟨-inf-58.86667⟩' WDSP = '⟨9.533333-18.266667⟩' \( \Rightarrow \) POST_MIN = low | 4 | 0.74481 |

### TABLE 12
Generated association rules for 24 hours before hot day prediction during summer months with support and confidence values

| Association Rule \( A \Rightarrow B \) | Support \( A \cup B \) | Confidence \( P(B/A) \) |
|----------------------------------------|-----------------|-----------------|
| MAX = '⟨90.8-104.6⟩' DEWP = '⟨72.533333-11.333333⟩' VISIB = '⟨6.766667-11.333333⟩' \( \Rightarrow \) POST_MAX = nor | 22 | 0.98956 |
| MIN = '⟨71.733333-80.666667⟩' DEWP = '⟨72.533333-11.333333⟩' WDSP = '⟨12.2-23.5⟩' \( \Rightarrow \) POST_MAX = nor | 20 | 0.98851 |
| MAX = '⟨90.8-104.6⟩' MIN = '⟨80.666667-Inf⟩' DEWP = '⟨-inf-64.566667⟩' WDSP = '⟨-inf-12.2⟩' \( \Rightarrow \) POST_MAX = nor | 5 | 0.95447 |
| MAX = '⟨104.6-inf⟩' MIN = '⟨71.733333-80.666667⟩' DEWP = '⟨72.533333-Inf⟩' \( \Rightarrow \) POST_MAX = high | 9 | 0.78364 |
| MAX = '⟨104.6-inf⟩' MIN = '⟨80.666667-Inf⟩' DEWP = '⟨72.533333-Inf⟩' WDSP = '⟨-inf-12.2⟩' \( \Rightarrow \) POST_MAX = high | 27 | 0.7781 |
TABLE 13
Generated association rules for 48 hours before hot day prediction during summer months with support and confidence values

| Association Rule \((A \Rightarrow B)\) | Support \((A \cup B)\) | Confidence \(P(B/A)\) |
|--------------------------------------|---------------------|---------------------|
| MAX = '(104.6-inf)' \(\Rightarrow\) MIN = '(80.666667-inf)' DEWP = '(64.566667-72.533333)' WDSP = '(-inf-12.2-23.5]' \(\Rightarrow\) POST_MIN = high | 12 | 0.97741 |
| MAX = '(90.8-104.6)' \(\Rightarrow\) MIN = '(80.666667-inf)' DEWP = '(64.566667-72.533333)' VISIB = '(-inf-6.766667)' WDSP = '(-inf-12.2]' \(\Rightarrow\) POST_MIN = nor | 296 | 0.83235 |
| MAX = '(90.8-104.6)' \(\Rightarrow\) MIN = '(80.666667-inf)' DEWP = '(64.566667-72.533333)' WDSP = '(-inf-12.2]' \(\Rightarrow\) POST_MIN = nor | 236 | 0.7757 |
| MAX = '(104.6-inf)' WDSP = '(-inf-12.2-23.5]' \(\Rightarrow\) POST_MIN = high | 22 | 0.69106 |
| MAX = '(104.6-inf)' MIN = '(80.666667-inf)' DEWP = '(72.533333-inf)' WDSP = '(-inf-12.2]' \(\Rightarrow\) POST_MIN = high | 27 | 0.60039 |

TABLE 14
Statistical summary of cold day and hot day prediction

| Measures | Cold day prediction | Hot day prediction |
|----------|---------------------|--------------------|
|          | 24 hour before | 48 hour before | 24 hour before | 48 hour before |
| Total number of instances | 2304 | 2304 | 2374 | 2373 |
| Correctly classified instances | 1827 | 1837 | 2093 | 2075 |
| Incorrectly classified instances | 477 | 467 | 281 | 298 |
| Correctly classified in % | 79.31 | 79.73 | 88.1634 | 87.4421 |
| Incorrectly classified in % | 20.69 | 20.27 | 11.8366 | 12.5579 |
| Mean absolute error | 0.2527 | 0.2832 | 0.1878 | 0.1991 |
| Root mean squared error | 0.3584 | 0.3697 | 0.3077 | 0.3179 |

(iii) Perform classification and obtain performance metrics.

(iv) Select the next partition as testing and use the rest as training data.

(v) Repeat classification until each partition has been used as the test set.

(vi) Calculate an average performance from the individual experiments.

The experience of many machine learning experiments suggest that using 10 partitions (tenfold cross-validation) often yields the same error rate as if the entire data set had been used for training. By using supplied test set method, forty-five years (1961-2005) of dataset is used as training set and remaining individual years 2006, 2007, 2008, 2009 and 2010 are used as testing set respectively. First the method is used to predict the wet and dry days. Then it is tested to predict the cold day of winter and hot days of summer.

Validation is done to find out the reliability of the generated results and to show whether they can be used in real time for the prediction of rainfall using the mining approach. Validation have been done through \(K^*\) methodology (Cleary and Trigg, 1995). For predicting rain occurrences, the statistical summary on SW and NE monsoon is shown in Table 5, the confusion matrix for positive and negative tuples of precipitation prediction describes in Table 6, the values of confusion matrix is shown in Table 7 and the detailed accuracy by class for precipitation prediction on SW and NE monsoon is described in Table 8. The validation results are shown in Table 9 using supplied test set method for the years 2006, 2007, 2008, 2009 and 2010 and these results are reasonable accurate. It is seen that the percentage of success in forecast is very satisfactory both in southwest and northeast monsoon seasons.

Next the methodology was tried to predict the very cold winter days and very hot summer days. The 20 °C (68 °F) was tacitly taken as threshold value for minimum temperature prediction (i.e., Cool day prediction) during
January and February of winter months and 38 °C (100.4 °F) as threshold for maximum temperature prediction (i.e., hot day prediction) during April and May of summer months. The cold day is considered when winter minimum is below the threshold value (i.e., 68 °F) and the hot day is considered when the summer maximum is above the threshold (i.e., 100.4 °F) were predicted. The mean daily maximum temperature, mean daily minimum temperature, wind speed, dew point and visibility are considered for the occurrence of the cold day and hot day prediction. A total of 2374 instances were used for hot day prediction after filtering operations were carried out, in this a total of 310 instances were the above threshold value 38 °C (100.4 °F). 2304 instances were used for analysis for cold day prediction, in this 481 instances were below threshold value 20 °C (68 °F). The weather patterns have been generated for the occurrence of the cold day during winter months using the above weather parameters. The correlations and relationships of cold day and hot day for 24 hours ahead and 48 hours ahead are shown in Tables 10-13. The statistical validation of cold and hot day prediction using 10-fold cross validation method with the predictor accuracy measures is shown in Table 14. The loss functions absolute error and mean squared error measure the error between the actual class and the predicted class. Here the weather patterns are also very encouraging.

5. Conclusions

A forecast for predicting wet and dry days during monsoon seasons as well as the cold day during winter and hot day in summer based on data mining technique has been proposed for a sample inland station, Trichirappalli of South India. The results are encouraging and interesting. The main advantage of this model is that we need ‘in-situ’ data only instead of data at different stations covering the region.

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