A Weather Forecasting Model using the Data Mining Technique

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ABSTRACT
The weather conditions are changing continuously and the entire world is suffers from the changing Clemet and their side effects. Therefore pattern on changing weather conditions are required to observe. With this aim the proposed work is intended to investigate about the weather condition pattern and their forecasting model. On the other hand data mining technique enables us to analyse the data and extract the valuable patterns from the data. Therefore in order to understand fluctuating patterns of the weather conditions the data mining based predictive model is reported in this work. The proposed data model analyse the historical weather data and identify the significant on the data. These identified patterns from the historical data enable us to approximate the upcoming weather conditions and their outcomes. To design and develop such an accurate data model a number of techniques are reviewed and most promising approaches are collected. Thus the proposed data model incorporates the Hidden Markov Model for prediction and for extraction of the weather condition observations the K-means clustering is used. For predicting the new or upcoming conditions the system need to accept the current scenarios of weather conditions. The implementation of the proposed technique is performed on the JAVA technology. Additionally for justification of the proposed model the comparative study with the traditional ID3 algorithm is used. To compare both the techniques the accuracy, error rate and the time and space complexity is estimated as the performance parameters. According to the obtained results the performance of the proposed technique is found enhanced as compared to available ID3 based technique.

Keywords
Data mining, classification, supervised learning, implementation, performance study.

1. INTRODUCTION
In recent years a number of new techniques and the new technologies are appeared. Among them the machine learning and data mining applications are producing their noteworthy contributions. In the various applications such as e-commerce recommendation, stock market prediction, spam filtering and others are developed with the help of data mining techniques. The data mining techniques are offered to analyse the historical data and prepare their experiences. This experience or the learning is used to identify the similar kind of data for classification task, or for making prediction and approximation. In this proposed work the machine learning based classification and prediction is studied in detail.

In addition of that using the data mining technique a new prediction model is prepared using the hybrid technique of machine learning. The proposed technique is a weather forecasting model; the proposed weather forecasting technique is analysing the historical weather data and the concerned attributes. These attributes are due points, moisture and others, these attributes are responsible for Clemet or weather conditions. Thus using these attributes analysis the weather forecast is performed. For evaluation of the attributes and identification of similar patterns the proposed technique includes both the supervised learning and unsupervised learning technique. Therefore the proposed technique is a hybrid technique of learning and prediction.

As discussed previously data mining techniques are helpful for various kinds of pattern extraction, objective recognition and prediction. These extracted meaningful patterns form the data helps for decision making, business intelligence and other technological task. Therefore a rich survey on the different data mining applications more specifically the predictive data modelling is performed. Based on the observations the data is more effective parameter by which the performance of any predictor is depends therefore the entire contribution is defined in three major domains. First the data pre-processing, in this phase the type of data is analysed and the key attributes are recognized. To do this the input data is first evaluated and the noisy contents and the missing data are handled. This approach helps to improve the quality of data for learning and pattern identification.

In next step the data model is prepared, in this phase the data attributes are used for design and development of the proposed data model. Therefore to analyse them the Hidden Markov Model and K-means clustering is utilized. The k-mean clustering is used to generate the observations from the input datasets. These observations are made on the basis of months available in database and the events or weather conditions. Similarly the transition matrix is prepared on the basis of the different weather conditions that are required to predict. Using these two matrixes the Hidden Markov Model is prepare their model for prediction. In next phase the prediction and performance evaluation is performed. Therefore the user input is taken and according to the current weather conditions the upcoming event is predicted.

2. ALGORITHM STUDY
This section includes the study of the different algorithms that are used for the developing the proposed model. The list of algorithms is given as:

2.1 K-Means
The K-Means clustering algorithm is a partition-based cluster analysis method. According to the algorithm we firstly select k objects as initial cluster centers, then calculate the distance between each object and each cluster center and assign it to the nearest cluster, update the averages of all clusters, repeat this process until the criterion function converged. Square error criterion for clustering

$$E = \sum_{i=1}^{k}\sum_{j=1}^{n_i}\left\|x_{ij} - m_i\right\|^2$$

$x_{ij}$is the sample j of i-class, $m_i$is the center of i-class, n_ii is the number of samples of i-class. K-means clustering algorithm is simply described as

Table 1 shows the K-mean algorithm steps

Input: N objects to be cluster (xj, Xz … xn), the number of clusters k;
Output: k clusters and the sum of dissimilarity between each object and its nearest cluster center is the smallest;
Process: 1. Arbitrarily select k objects as initial cluster centers $(m_1, m_2, \ldots, m_k)$; 2. Calculate the distance between each object Xi and each cluster center, then assign each object to the nearest cluster, formula for calculating distance as: $d(x_i, m_i) = \sqrt{\sum_{j=1}^{d}\left(x_i - m_{j1}\right)^2}, i = 1 \ldots N, j = 1 \ldots k$ $d(x_i, m_i)$is the distance between data i and cluster j. 3. Calculate the mean of objects in each cluster as the new cluster centers, $m_i = \frac{1}{N}\sum_{j-1}^{n_i} x_{ij}, i = 1,2, \ldots, K$ N_i is the number of samples of current cluster i; 4. Repeat 2) 3) until the criterion function E converged, return$(m_1, m_2, \ldots, m_k)$ Algorithm terminates.

2.2 HMM

An HMM is a double implanted stochastic process with two hierarchy levels. It can be used to model much more complex stochastic processes as compared to a traditional Markov model. In a specific state, an observation can be generated according to an associated probability distribution. It is only the observation and not the state that is visible to an external observer. An HMM can be characterized by the following:

1. N is the number of states in the model. We denote the set of states' S = {S_1; S_2;..., S_N}, where S_i, i= 1;2;...;N is an individual state. The state at time instant t is denoted by qt.
2. M is the number of distinct observation symbols per state. We denote the set of symbols

   V = {V_1; V_2; ...V_M}, where V_i, I = 1;2;...; M is an individual symbol.
3. The state transition probability matrix A = [a_{ij}], where
   $$a_{ij} = P\left(q_{t+1} = S_j \middle| q_t = S_i\right), 1 \le i \le N, 1 \le j \le N; t = 1,2 \ldots$$

   Here a_{ij}> 0 for all i, j. Also,
   $$\sum_{j=1}^{N} a_{ij} = 1, 1 \le i \le N$$
4. The remark symbol probability matrix B = {$b_j(k)$}, where
   $$b_j(k) = P\left(V_k \middle| S_j\right), 1 \le j \le N, 1 \le k \le M \wedge$$
   $$\sum_{k=1}^{M} b_j(k) = 1, 1 \le j \le N$$
5. The initial state probability vector rπi , where
   $$\pi_i = P(q_1 = S_i), 1 \le i \le N$$

   Such that
   $$\sum_{i=1}^{N} \pi_i = 1$$
6. The remark sequence O = O_1; O_2; O_3; ...O_R, where each remark O_t is one of the symbols from V, and R is the number of remarks in the sequence.

It is manifest that a complete specification of an HMM needs the approximation of two model parameters, N and M, and three possibility distributions A, B, and π. We use the notation ^ = (A; B;π) to specify the complete set of parameters of the model, where A, B implicitly contain N and M.

An observation sequence O, as mentioned above, can be generated by many possible state sequences. Consider one such particular sequence Q = q_1; q_2; ...; q_R; where q1 is the initial state. The probability that O is generated from this state sequence is given by

$$P(O|Q,\lambda) = \prod_{t=1}^{R} P(O_t \vee q_t, \lambda)$$

Where statistical independence of observations is assumed Above Equation can be expanded as

$$P(O|Q,\lambda) = b_{q1}(O_1)b_{q2}(O_2) \ldots \ldots b_{qR}(O_R)$$

The probability of the state sequence Q is given as

$$P(Q|\lambda) = \pi_{q1}a_{q1q2}a_{q2q3} \ldots \ldots a_{qR-1qR}$$

Thus, the probability of generation of the observation sequence O by the HMM specified by can be written as follows:

$$P(O|\lambda) = \sum_{allQ} P(O|Q,\lambda)\, P(Q \vee \lambda)$$

Deriving the value of $P(O \vee \lambda)$ using the direct definition of is computationally intensive. Hence, a procedure named as Forward-Backward procedure is used to compute$P(O \vee \lambda)$.

3. PROPOSED WORK

The proposed data model is provided using the figure 1. In this diagram the different components of predictive data model is demonstrated. These components are used for organizing the complete system therefore the detailed subcomponents are described as:-

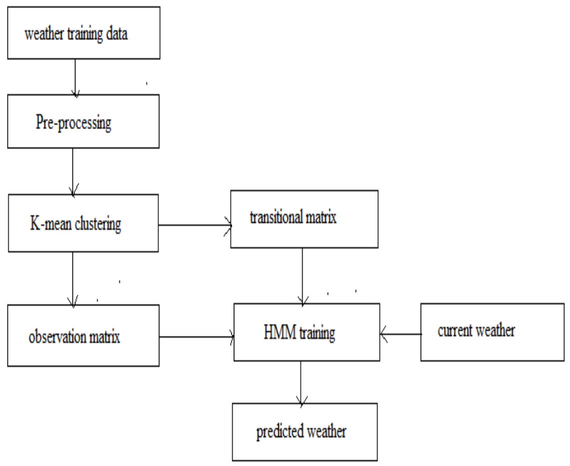

Figure 1 proposed technique

3.1 Weather Training Data

The supervised algorithms are working on labelled data. Such kind of data most of the time found in structured format. This structured data has some pre-defined class labels that are representing the outcomes of the combination of attributes. Thus using the training data the algorithm learned on pre-defined patterns. In this presented work the Bhopal weather forecasting data for last five years are used. That training dataset contains the different weather attributes observations and the class labels as the weather conditions.

3.2 Pre-processing

The pre-processing is a technique by which the data is refined, transformed and cleaned for improving the quality of the training data on which the data model is prepared for decision making or prediction. In this given technique the three major contributions is placed in this phase.

3.2.1 Removal of attributes that are not fluctuating with the other patterns

In this phase those attributes are removed from the training samples which are not fluctuating with the different data patterns. Thus this technique reduces the dimension of the dataset by which the memory consumption of the data analysis is reduces.

3.2.2 Removal of attributes that uniquely defined the instance data

In this phase the data set is evaluated for removal of data that are performing the identity representation for the dataset objects.

3.2.3 Missing data handling

In this phase the data is analyzed for finding the missing attributes in the data set. That also improves the quality of data for representation of accurate data model. Therefore those dataset objects are removed which are not completed or having the missing attributes.

3.3 K-means clustering

In this phase the well refined and defined data is used for prepare the groups of the data which are simulating the similar behavioural patterns. Therefore the entire data is clustered according to the similar attributes in these grouping of data the data attributes are considered. The outcome of the k-means clustering is organized in two main matrixes given as.

3.4 Observation matrix

That is the matrix on which the clustered data is arranged in order to develop the observation matrix of the Hidden Markov Model. Therefore the clustered data is 12 groups are considered as the observations. Additionally the data objects class labels are recognized here as the states of the events. These states are the natural events or the weather conditions which are required to predict. Thus for the different clustered observations O= $\{o_1, o_2, \dots, o_{12}\}$ and similarly the weather conditions W=$\{w_1, w_2, \dots, w_n\}$. The matrix is developed as given in table 2.

Table 2 Example observation matrix

	o_1	o_2
w_1		
w_2		

3.5 Transition matrix

As discussed previously the output of k-means clustering is organized in two matrixes the first observation matrix is given using the table 2 which includes the probability distribution of the weather conditions in the observations. In this transition matrix the weather conditions and next weather conditions are organized on the basis of the matrix. Let's the weather conditions W=$\{w_1, w_2, \dots, w_n\}$. Then the transition matrix is given by table 3.

Table 3 Example transition table

	w_1	w_2
w_1		
w_2		

3.6 HMM training

The hidden Markov model is responsible to accepting these two matrixes as input and producing the learned model for prediction. The Hidden Markov model is trained in this phase for the given observational patterns and the transitional patterns.

3.7 Current weather

In order to predict the next weather condition or upcoming weather condition the system required to take input the just patterns of the weather conditions, based on the observation and transitional patterns the system generate the next possible pattern of weather condition.

3.8 Predicted weather

That is the final outcome of the proposed data model as the predictive outcome.

3.9 Proposed algorithm

The given section summarizes the entire process models into the procedural steps. Thus the section introduces the proposed algorithm for prediction using table 4.

Table 4 Proposed Algorithms

Input: training dataset D, current weather conditions C Output: predicted weather condition P
Process: 1. O= Read_Training_data(D) 2. $[M_o, M_t]$ = Kmeans_Clustering(O, 12) 3. T = HMM.Train(M_o, M_t) 4. P = HMM.Predict (T, C) 5. return P

4. RESULTS ANALYSIS

The given section provides the understanding about the evaluated results and parameters. These parameters are shows the effectiveness of the proposed technique.

4.1 Training Time

The amount of time consumed during the training of the system is termed as the training time of the algorithm. That is also termed as the training time complexity for the algorithm.

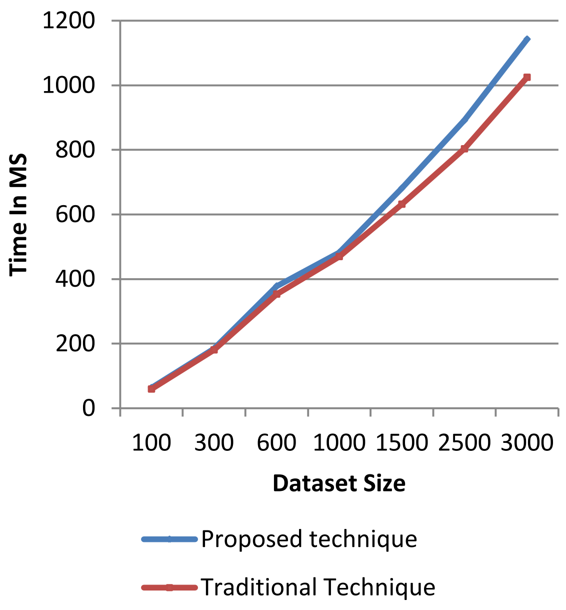

Figure 2 training time

Table 4 training time

Dataset Size	Proposed technique	ID3 decision tree
100	63.4	59.21
300	184.7	180.43
600	378.1	353.15
1000	482.32	469.41
1500	681.45	631.52
2500	891.38	803.04
3000	1142.43	1024.41

Figure 2 and the table 4 shows the training time of the algorithms in terms of milliseconds. Additionally during the experimentation, the performance of algorithms with the size of dataset is increases or decreases are reported. In order to represent the performance of system the X axis of diagram contains the dataset size and the Y axis shows the estimated time in milliseconds.

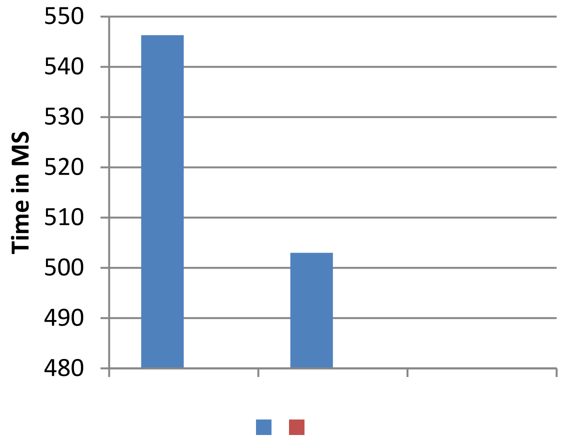

Figure 3 mean training time

According to the obtained results the traditional algorithm namely ID3 decision tree algorithm consumes less time as compared to the proposed algorithm. This because for improving the accuracy in prediction of the system needs to calculate the additional parameters as compared too traditional method. Thus the time complexity of proposed algorithm is higher as compared to traditional system. To clearer view of the data modelling the mean training time of both the techniques are evaluated and compared using figure 3. In this diagram the X axis contains the methods implemented with the system and Y axis shows the mean training time of the algorithms. According to the results analysis the performance of traditional algorithm is better than the proposed algorithm in terms of mean training time.

4.2 Prediction time

The amount of time required to evaluate the data form making accurate prediction is termed here as the prediction time. That prediction time of both the system in comparative manner is demonstrated using figure 4 and the table 5. In this diagram the amount of data is given in the X axis and the Y axis shows the performance obtained in terms of milliseconds. According to observations the amount of time during prediction is not much fluctuated and not also affected by the amount of data to be process. The comparative results of the systems shows the effectiveness of the proposed technique that consumes less time for computing the predicted events as compared to traditional approach. Because during the time based data clustering reduces the amount of data to process. Thus the prediction is much frequent as compared to the traditional approach.

Table 5 comparative prediction time

Dataset Size	Proposed technique	ID3 algorithm
100	19.37	27.47
300	21.66	37.17

600	20.61	33.42
1000	38.13	36.83
1500	26.51	40.52
2500	33.24	45.21
3000	32.01	41.13

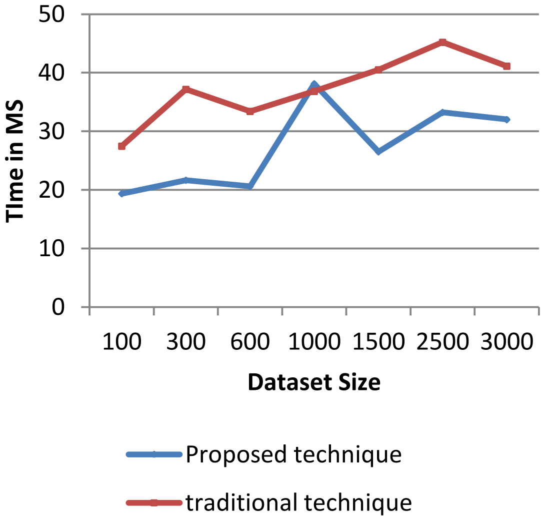

Figure 4 prediction time

In order to clarify the difference among the traditional and proposed technique the mean prediction time of both the technique is evaluated and compared using the figure 5.

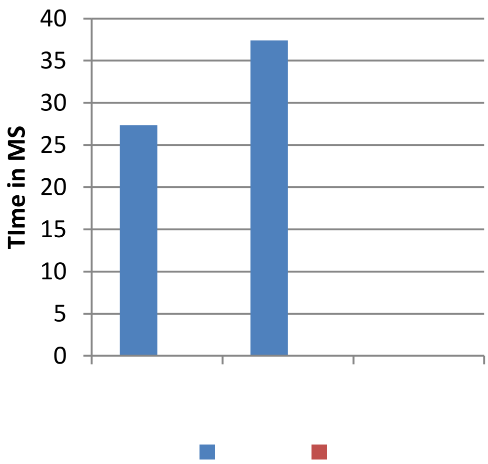

Figure 5 mean prediction time

In this diagram the X axis shows the implemented techniques and the Y axis shows the computed time in terms of milliseconds. According to the obtained results the performance of the proposed technique is improved as compared to traditional approach of weather forecasting.

4.3 Memory used

The memory consumption shows the amount of main memory required to process the algorithm task. That is also called the space complexity of the system.

Table 6 memory consumption

Dataset Size	Proposed technique	Traditional technique
100	30992	31773
300	31648	32937
600	33827	34912
1000	35711	37811
1500	36837	38817
2500	38271	39721
3000	39813	41019

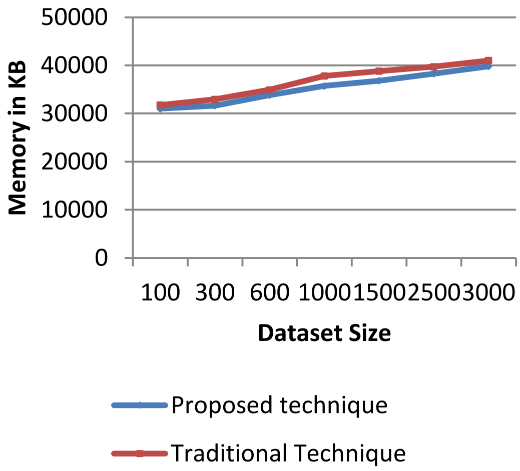

Figure 6 memory consumption

That is also known as the space complexity in algorithm study. The figure 6 and table 6 shows the memory consumption of the system with increasing size of training dataset. The amount of data is given using the X axis and the Y axis shows the amount of consumed memory during experimentation with respective amount of data in terms of kilobytes. According to the experimented results the amount of memory is similar and not more fluctuating. But the respective comparison the proposed algorithm is efficient than the traditional approach of prediction. In order to investigate the difference in the memory consumption of the proposed and traditional technique the mean memory consumption is calculated and reported using the figure 7. In this diagram the X axis contains the methods name and the Y axis contains the mean memory consumption of the system.

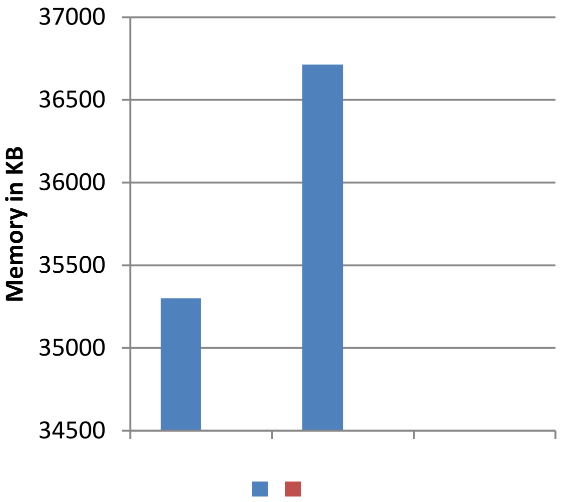

Figure 7 mean memory consumption

4.4 Accuracy

The accuracy of the predictive algorithm provides the amount of generated prediction is similar to actual outcomes. Therefore that can also be defines as the amount of correctly recognized patterns among the total samples produces to test. That can also be evaluated using the following formula:

$$accuracy = \frac{totalcorrectlyidentifiedpatterns}{totalinputsamples} X100$$

The figure 8 and table 7 contains the evaluated performance of the system in terms of algorithm accuracy of prediction. In this diagram the amount of accurate pattern recognition is given using Y axis and the X axis shows the amount of data to be train for the predictor. According to the comparative results the performance of the proposed algorithms remains much consistent and increasing as compared to the traditional algorithm. In order to evaluate the accuracy of algorithm a fixed amount random patterns are extracted from database and the next values are used as the actual class label during evaluation of data. for finding the difference among both the predictive algorithm's accuracy the mean accuracy of both the

Table 7 accuracy

Dataset Size	Proposed technique	ID3 Algorithm
100	78.53	75.25
300	82.47	77.52
600	85.21	78.93
1000	87.45	80.29
1500	89.52	81.83
2500	90.12	83.21
3000	93.28	84.63

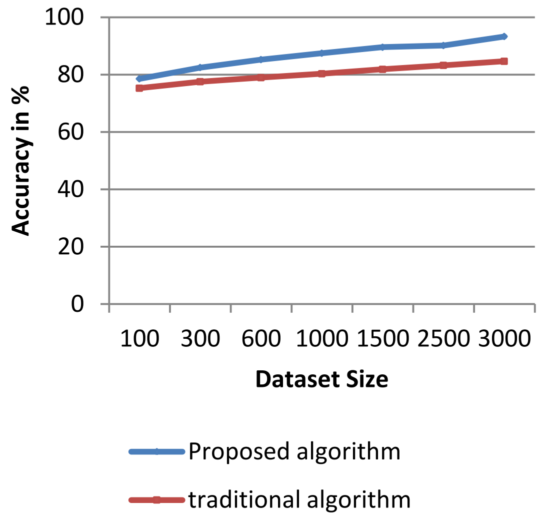

Figure 8 accuracy

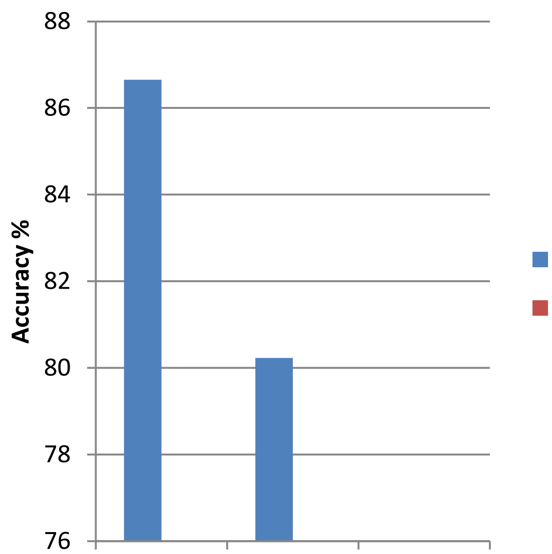

Figure 9 Mean accuracy

Algorithms are computed and demonstrated using the figure 9. In this diagram the X axis contains the techniques implemented and the Y axis shows the percentage accuracy of the algorithms. According to the obtained performance the proposed technique produces higher accurate results as compared to traditional weather forecasting model.

4.5 Error rate

The error rate of the predictive system demonstrates the amount of data which is not correctly recognized during the testing. Therefore that can be computed using the following formula:

$$errorrate = \frac{\substack{totalpatterns \\ totalincorrectlyidentifiedpattern}}{} identifyX100$$

Or

$$errorrate = 100 - accuracy$$

The computed error rate percentage of both the implemented techniques is given using figure 10 and the table 8. In the given diagram the X axis shows the amount of data used for training and the Y axis shows the percentage error rate obtained. According to the experimental results the performance of the proposed classification algorithm is improved much rapidly as compared to the traditional technique. Therefore the error rate of the system is reduces as the amount of data for classification is increases or training data is increases.

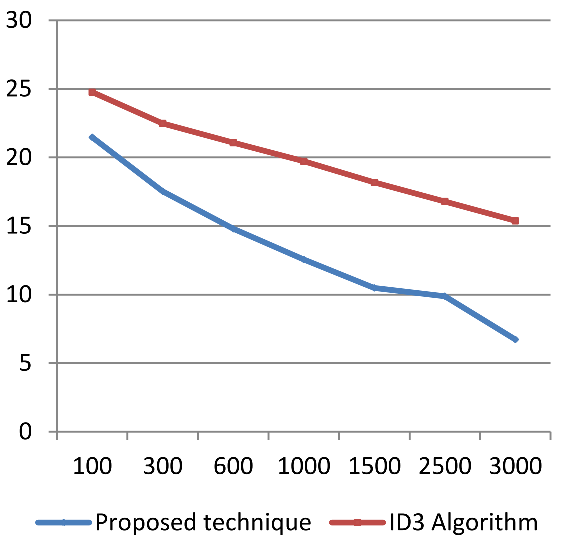

Figure 10 error rate percentage

Table 8 error rate percentage

Dataset Size	Proposed technique	ID3 Algorithm
100	21.47	24.75
300	17.53	22.48
600	14.79	21.07
1000	12.55	19.71
1500	10.48	18.17
2500	9.88	16.79
3000	6.72	15.37

In order to differentiate the error rate computation for predicting the weather the mean error rate is measured and reported using the figure 11. In this diagram the X axis shows the implemented algorithms and the Y axis shows the error rate percentage. According to the obtained results the error rate of the traditional algorithm is higher as compared to the proposed technique thus the performance of the proposed technique is improved from the traditional technique.

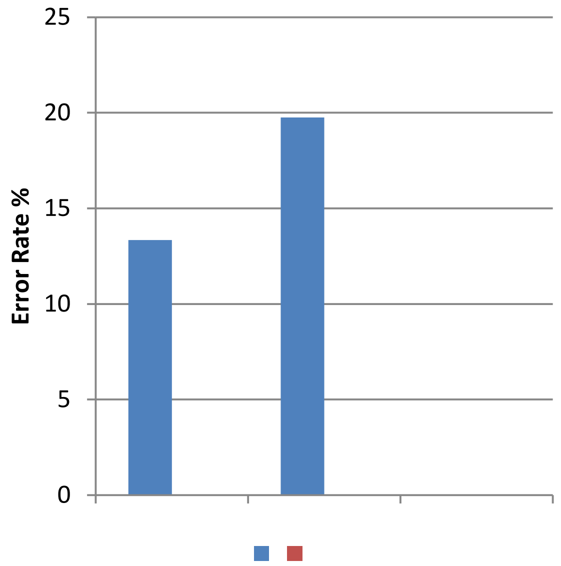

Figure 11 mean error rate

5. CONCLUSION

The key aim and objective of the proposed work is accomplished and a predictive data model is prepared. In this chapter the summary of the proposed technique is provided and their experimentation based and observation based facts are reported in this section. Additionally for the future extension some key facts are also suggested to implement with the system.

5.1 Conclusion

The proposed work is intended to find the solution for accurate weather data modeling and prediction using the historical data. Therefore the data mining technique is studied for developing such kind of data model. The data mining techniques analyse the data of some pre-defined pattern and extract the significant on the data. Using the extracted patterns from the data the model takes training and prepared for classifying or predicting the similar patterns of associated class labels. The classification of the data supported by supervised technique of data mining. The key issue in weather prediction is to accomplish the relationship among the class labels and the attributes which are used for predicting the weather conditions. Therefore using the available accurate techniques a new data model is developed for weather forecasting.

The proposed weather forecasting data model utilizes the k-means unsupervised learning technique for performing the clustering on the entire training dataset. This clustering is performed for finding the pattern level pattern similarity among two instance data. The total number of 12 clusters is developed; these clusters are providing the observations of the data and their weather conditions. Using the extracted observations and available class labels the data is re-organized in terms of observation matrix and the transition matrix. These two different matrixes are provided into next phase namely Hidden Markov Model and the training are performed. The trained data model is used for prediction or the pattern recognition work. For making the prediction, using prepared trained data model. The system needs to provide the current weather conditions on the basis of that the new upcoming pattern of data is predicted.

The implementation of the proposed technique is performed using the JAVA development technology and their performance is evaluated. The performance of the proposed technique is given by the accuracy, error rate and the time and space complexity. The performance summary of the proposed data model is given using the table 9.

Table 9 Performance Summary

S. No.	Parameters	Proposed technique	Traditional ID3
1	Accuracy	High	Low
2	Error rate	Low	High
3	Memory consumption	Low	High
4	Training time	High	Low
5	Prediction time	Low	High

According to the obtained results the proposed technique is efficient and accurate for weather prediction and data modeling. Thus that is adoptable for classification and prediction for the event based data and their approximation.

5.2 Future work

The key aim for improving the classification and prediction performance for the traditional weather prediction model is designed and developed in this work. The implemented technique is efficient and accurate for weather prediction but some limitations of the model is also observed thus in near future need to be review before use of the proposed technique. Some of the key extensions of the works are as follows:

1. **Need to improve the training time:** the training time of the proposed data model is increases with the amount of data to be trained.
2. **Need to be increasing the training samples for collecting the training data:** as the performance of prediction is increases with the amount of data thus huge data can solve the issues of incorrect classification or prediction..

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