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Weather Forecasting Prediction Using Ensemble Machine Learning for Big Data Applications

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Abstract: The agricultural sector's day-to-day operations, such as irrigation and sowing, are impacted by the weather. Therefore, weather constitutes a key role in all regular human activities. Weather forecasting must be accurate and precise to plan our activities and safeguard ourselves as well as our property from disasters. Rainfall, wind speed, humidity, wind direction, cloud, temperature, and other weather forecasting variables are used in this work for weather prediction. Many research works have been conducted on weather forecasting. The drawbacks of existing approaches are that they are less effective, inaccurate, and time-consuming. To overcome these issues, this paper proposes an enhanced and reliable weather forecasting technique. As well as developing weather forecasting in remote areas. Weather data analysis and machine learning techniques, such as Gradient Boosting Decision Tree, Random Forest, Naive Bayes Bernoulli, and KNN Algorithm are deployed to anticipate weather conditions. A comparative analysis of result outcome said in determining the number of ensemble methods that may be utilized to improve the accuracy of prediction in weather forecasting. The aim of this study is to demonstrate its ability to predict weather forecasts as soon as possible. Experimental evaluation shows our ensemble technique achieves 95% prediction accuracy. Also, for 1000 nodes it is less than 10 s for prediction, and for 5000 nodes it takes less than 40 s for prediction.

Keywords: Weather; forecasting; KNN; random forest; gradient boosting decision tree; naive bayes bernoulli

1 Introduction

In Meteorological data, a huge volume of data is collected by various sensors for the prediction of weather forecasting. Gathering such big data is a vital process that aids people's day-to-day activities. Prediction of weather conditions is essential for human beings to plan mitigation measures for them from harmful weather conditions. It is also useful in many areas, including decision-making, agriculture, tourism, and business [1,2]. Big Data contains tremendous weather information in an unstructured, semi-organized format. Handling this unstructured data is a difficult task to process and store. Therefore, a machine learning technique is implemented. The current prediction of weather forecasting models depends on complicated physical models which need high-performance computer systems with many HPC nodes for the implementation of the prediction systems. Despite the employment of high-performance computers and high-speed communication lines, such systems yield erroneous forecasts or an incomplete understanding of atmospheric processes. Furthermore, running such a sophisticated model takes more time [3]. To address the drawbacks of existing models, the proposed method employs a variety of algorithms and ensembles them using a maximum voting mechanism. It is reliable, accurate, and has a minimum prediction time and error rate.

Machine learning methods are also used in weather forecasting classification. There is machine learning techniques exist that have the ability to predict the weather conditions such as rainfall, wind speed, wind direction, and temperature. Random forest, KNN, Gradient boost algorithm, decision tree, and other machine learning techniques are combined to build a machine learning algorithm, which is referred to as an ensemble-based technique. The advantage of using the ensemble-based technique is to increase the prediction accuracy and produces better results.

The main contributions of our proposed ensemble-based weather forecasting (EBWF)model are:

- An ensemble-based prediction technique is proposed for enhanced weather prediction performance.
- Gradient boosting technique is developed for identifying relevant features for accurate weather prediction. This feature selection approach requires minimum time complexity.

This article is organized as follows: Section 2 provides a review of several research literature, Section 3 describes the prediction of weather forecasting using an ensemble-based approach of max voting, Section 4 discusses the results, and Section 5 concludes the research with future directions.

2 Literature Review

The use of classical and deep learning algorithms to forecast weather temperature has been widely investigated in the literature. The majority of the work relies on supervised learning techniques. Historical data of meteorological factors such as past temperature and wind speed and direction are used to forecast the weather. The support vector machine (SVM) and artificial neural network (ANN) are the most common models used in weather forecasting so far. The capacity of CNN to deal with non-linear and high-dimensional data is well-known. SVM is noted for its accuracy and resilience. Based on previous studies, prior temperature, relative humidity, solar radiation, rain, and wind speed observations are the top attributes for forecasting temperature among the available meteorological attributes. Among the most commonly utilized performance measurements are Mean Squared Error

(MSE) and Mean Absolute Error (MAE). Notice that some models are dedicated to predicting hourly temperatures whereas others predict longer-term temperatures such as 24 h ahead [4].

The authors in [5] released a publicly available weather dataset and conducted simple models as a baseline enabling others to run new models and compare their findings with the existing models to further research in weather prediction up to several days ahead. The dataset includes weather data between 1979 and 2018. The dataset includes features such as temperature, humidity, wind, cloud cover, precipitation, and solar radiation. In addition to constant variables such as the soil type, longitude, and latitude. Regression, deep learning, and physical prediction models are among the baseline models presented in the study. The outcomes of the experiments are reported using several performance metrics. When dealing with weather forecasts, the authors recommend utilizing a successive period of time for testing and validating the models rather than using random samples of data. Therefore, the authors used the year 2016 for validating the performance of their models, the years 2017 and 2018 for testing, and all years from 1979to 31 December 2016 for training the models. The authors mentioned some challenges and future directions for research and that included, selecting the best combination of features, applying different machine learning techniques, dealing with big data, and having larger weather datasets to improve weather forecasting.

The WRF model (Weather Research and Forecasting) is a complex numeric weather prediction model. Short-term and long-term prediction models were implemented using the deep learning models named long short-term memory (LSTM) and temporal convolutional network (TCN) [6]. The results are compared with the WRF model. LSTM and TCN models were first implemented for short-term weather forecasts. They were then fine-tuned for long-term predictions. The study proposes two different forms of models. The first model employs a single network with 10 inputs and outputs. That is, it predicts future values of all-weather predictors based on their historical values. The second model, on the other hand, implies 10 separate networks, each with ten inputs and only one output. This indicates that each network receives historical values for all-weather attributes, but only forecasts the future value of one attribute at a time. The training dataset includes the duration from January to May 2018. The testing data covers the period of June 2018 while the validation set includes the period of July 2018. The results show that proposed deep learning-based models outperform the WRF model with the advantage of having a lightweight model compared to WRF. They also show that having a network for each prediction produces better results than having one network that produces all the forecasts.

The proposed model in [7] combines numerical weather prediction (NWP) with historical data to forecast the weather. The study uses deep learning called the deep uncertainty quantification model (UQM) and optimizes its performance by using a loss function that is based on the negative log-likelihood error (NLE). The data is pre-processed. First, records with entirely missing data are deleted otherwise linear interpolation is used to impute missing data. Continuous features are normalized using min-max normalization into [0, 1]. Categorical data are encoded by embedding. Three weather features are used in the proposed model which are the temperature and relative humidity at 2 meters and wind at 10 meters. Tab. 1 describes that survey on the prediction of Weather forecasting.

Table 1: Survey on attributes and prediction techniques of weather forecasting

Author	Attributes	Technique	Prediction
Abdel-Kader et al. [1] (2021)	Temperature, humidity, wind speed	Multilayer perceptron with particle swarm optimization	Prediction of rainfall
Basha et al. [8], (2020)	Temperature, humidity, wind speed, wind direction	ANN, SVM, MLP Model, Auto-Encoders	Prediction of rainfall
Huang et al. [9] (2020)	Temperature, humidity, air pressure	LSTM, MLP	Prediction of air pressure
Mohammed et al. [10] (2020)	Measurement of Rainfall	Multi-Linear support vector regression and lasso regression	Prediction of rainfall
Suresha [11] (2020)	Humidity, Vapour Pressure	K-means clustering, Linear Regression, Multivariate Multiple Linear Regression	Prediction of rainfall
Yen et al. [12] (2019)	Humidity, pressure, wind speed and direction, temperature, rainfall, sea level,	Echo state-based network (ESN), Deep Echo state-based network (Deep ESN)	Prediction of rainfall
Singh et al. [13] (2019)	Temperature, humidity, and pressure	Random forest	Prediction of rainfall
Parashar [14] (2019)	Dust particles, pressure, humidity, rainfall, temperature.	Multiple linear regression	Prediction of Temperature
Mahabub [15] (2019)	Rainfall, humidity, temperature, and wind speed,	Support vector and linear regression, bayesian ridge, Gradient Boosting (GB), Extreme GB	Prediction of rainfall, wind speed.

3 Proposed Methodology

The proposed framework has been developed with all components including weather data collection, pre-processing, feature selection, ensemble-based evolutionary model building, and evaluation of the prediction results. Fig. 1 explains the weather forecasting proposed framework. Ensemble learning is an advanced machine learning technique that combines the results of several machine learning algorithms. This will lead to a better prediction of weather forecasting compared to single machine learning algorithms.

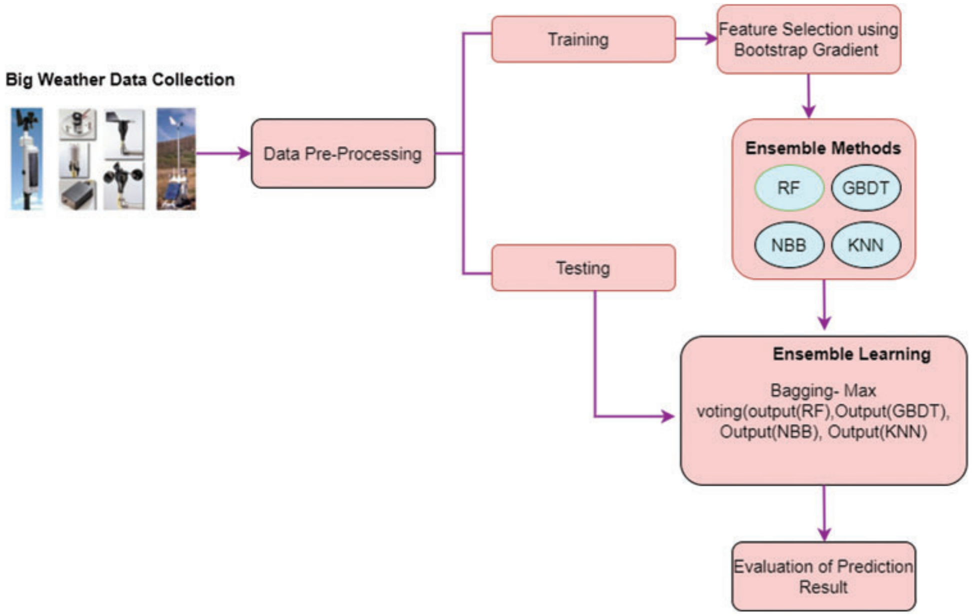

Big Weather Data Collection
Data Pre-Processing
Training
Testing
Feature Selection using Bootstrap Gradient
Ensemble Methods
RF
GBDT
NBB
KNN
Ensemble Learning
Bagging- Max voting(output(RF),Output(GBDT), Output(NBB), Output(KNN)
Evaluation of Prediction Result

Figure 1: Weather forecasting framework

The weather data set is divided into training data and testing data. The data is pre-processed to fill missing values and perform data normalization. The features are identified using gradient boosting which uses a gradient descent algorithm. The selected features are then classified using ensemble machine learning (ML) algorithms such as random forest, gradient boosting decision tree, Naive Bayes Bernoulli, and k-nearest neighbor (KNN) Algorithm to predict weather conditions. The prediction results of the above algorithms are ensemble using the bagging method which is called max-voting for the final prediction result.

3.1 Data Collection

The data is collected from various airport weather stations in India [16–18]. This dataset includes various attributes of air temperature, atmospheric pressure, humidity, the direction of the wind, and other variables. The sample attribute of weather data is given in Tab. 2. The experiments are implemented using Python version 3.7.3 with the Tensorflow version. The dataset includes contains 2006–2018 with 9 Features. Our model forecasts the weather 3 h ahead of time. The training dataset includes all features from the year 2006-to 2016. The testing dataset includes the years 2017 and 2018 with selected features in the dataset. Fig. 2 shows the feature representation of the weather data set in every 3 h which contains 27 features.

Table 2: Sample weather data set attributes

Attributes	Upper bound	Lower bound
f1_Longitude	130.87	33.51
f2_Latitude	37.43	33.51
f3_Height		

(Continued)

Table 2: Continued

Attributes	Upper bound	Lower bound
f4_ wind direction for 10 min (0.1 deg)	3500	0
f5_ wind velocity for 10 min (0.1 m/s)	423	0
f6_temperature for 1 min (0.1 C)	498	−398
f7_ humidity for 1 min(0.1%)	1000	0
f8_atmospheric pressure for 1 min(0.1 hPa)	10907	0
f9_ pressure in sea level (0.1 hPa)	11163	0

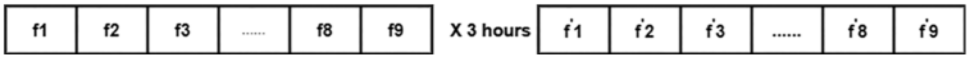


Figure 2: Feature representation for every 3 h

3.2 *Pre-Processing*

The collected weather dataset contains invalid or empty values. Therefore, the pre-processing stage is necessary. This stage includes data cleaning, data normalization, and one-hot encoding. Fig. 3 shows the phases of pre-processing.

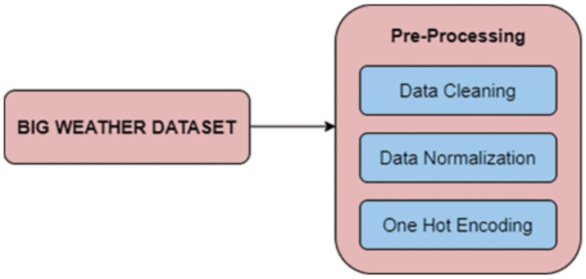


Figure 3: Phases in pre-processing

In data cleaning, raw weather data contains noise, inconsistent values, and missing values which affect the accuracy of the weather forecasting. In order to improve the quality and performance of the result. The null values are identified and eliminated from the data set. In this work, Min-Max normalization is used. The weather dataset is scaled into a range normalization] or [−1, 1]. This Min-Max normalization meta attributed the input of the attribute values o d_{norm} and the range of val is between $[min, max]$ by using the following formula:

$$d_{norm} = \frac{(max - min) * (d - low)}{high - low} \tag{1}$$

Here *max* is the maximum value of the selected attribute and *min* is the minimum value of the selected attribute. d_{norm} is the newly selected feature after applying the normalization. The benefit of normalization is to have data consistency.

One hot encoding converts the categorical feature of wind direction and its condition with dummy variables. This conversion is needed in the training and testing data set for keeping the same number of attribute features. That is by giving 1 for the presence of attribute and 0 for the absence of the attribute in the dataset.

3.3 Feature Selection

There are various feature selection algorithms like information gain, correlation, gain ratio, and so on. Such algorithms are used to identify important features from the whole feature set. This proposed concept uses an ensemble learning method called gradient boosting for relevant features selection. The bootstrap samples are independent and distributed evenly with the minimum correlation between the sample weather data. The gradient boosting technique uses gradient descent steps to reduce the loss while including input data into the ensemble model. Gradient descent is similar to the random forest but different in the way that samples are chosen without replacement.

Algorithm 1: A bootstrapped gradient boosting

Input: Pre-processed dataset
Output: Selected features
Step 1: Randomly select the features subset from the pre-processed features.
Step 2: *for* $i = 1$ *to* d // training data sample
Step 3: For all iteration *iter* the gradient boosting generates the new subset which includes an estimator called e to create the better subset model. The e is represented as,

$$F_{(t+1)}(d) = F_t(d) + e(d) = Y \ (targ) \tag{2}$$

$$e(d) = y - F_t(d) \tag{3}$$

Step 4: The calculated weight after each iteration in the Eq. (4)

$$\Delta we_i = -\eta \frac{\delta C}{\delta we_i} \tag{4}$$

where cost function $C(We) = \frac{1}{2}\sum_i (targ^i - out^i)^2$ and η-Learning rate which is updated over time as,

$\eta(t+1) = \dfrac{\eta(t)}{(1 + t \times d)}$ where d–decreasing constant

Step 5: update weight as

$$we_i := we_i + \Delta we_i \tag{5}$$

Step 6: end for
Step 7: Selecting the relevant feature from the dataset is based on the rank order of weight value in descending order. The top highest weight value is selected as relevant sub-features. After implementing Algorithm 1, it selected important features from the whole set of features in the dataset every 3 h. The selected important features are f4, f5, f6, f7, f8 were selected from the dataset.

3.4 Ensemble Learning Method

Ensemble methods are a combination of various algorithmic models. In our proposed model, we combine the results of Random Forest (RF) [19], Gradients Boosting Decision Tree (GBDT), Naïve Bayes Bernoulli (NBB), and KNN Algorithmic model. The final prediction outcome uses the outcome of the above algorithms which are then ensemble by max voting to produce a better result.

3.4.1 Random Forest

The random forest is a decision tree ensemble method in which weather data samples are classified based on many sub-trees. A classification outcome is generated for each tree which are then ensemble. Random Forest is similar to decision trees,

$$t\left(x,\theta_n\right)\ for\ n=1,2\ldots N \tag{6}$$

where θ_n-is an independent and identical distribution of random samples. Each prediction class K trees is given to a data sample D. The construction of the subset of decision tree is based on the following formula,

$$D=\{(x_i,y_i)\}\ \left(|X|=n,x_i\in R^m,\ y_i\in R\right. \tag{7}$$

The prediction probability of each subset is as follows,

$$prob\left(pc|F\right)=pc_1+pc_2+\ldots+cp_n\sum_{i=1}^{n}\left(pc_i\left(pc|F\right)\right) \tag{8}$$

where pc-is the prediction class, F-are the features, $pc_{1,}\ pc_2,\ldots,\ \ and\ pc_n$ is the probability of each feature in the dataset, n is the number of subsets, and the error is calculated as,

$$err\le\frac{corr\left(1-s^2\right)}{s^2} \tag{9}$$

Here $corr$ is the correlation between the trees and s is the parametric strength of the tree. The random forest classifier is shown in Fig. 4. In the training dataset, n is the subset of the decision tree which is partitioned and a prediction is calculated for every tree. In Fig. 3 the prediction of each tree is shown in different colour. As a whole, the average of all subsets of the trees' prediction result is considered as the final prediction class of the random forest.

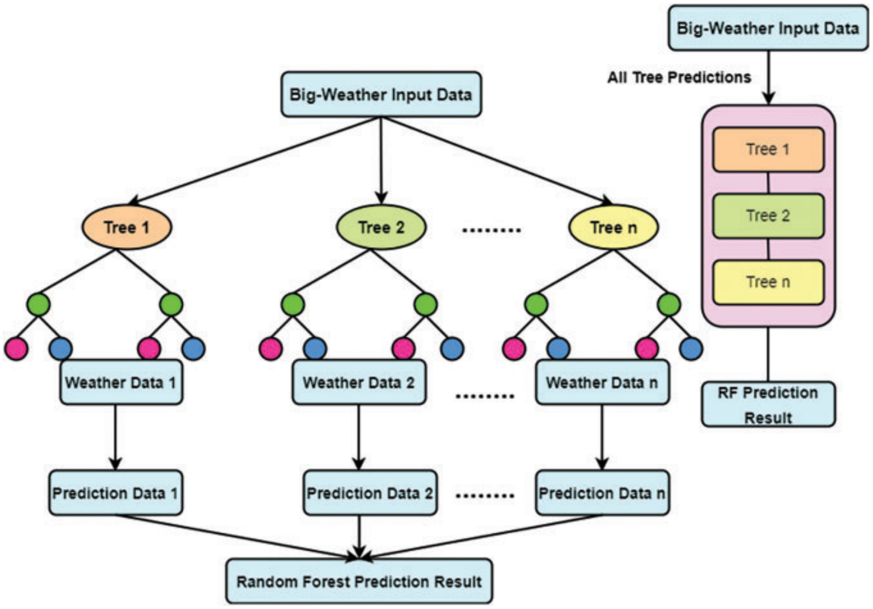


Figure 4: Random forest

3.4.2 Gradient Boosting Decision Tree (GBDT)

This approach works like machine learning techniques and effective in the prediction of weather forecasting. It gathers large volume of weak models and changes the modules' weight sample in every single step. GBDT is an ensemble boosting technique that iteratively generates decision trees based on its new regression value. This newly generated regression decision tree is used to fit the error in the classification of weather input dataset in every step of the process. The purpose of using GBDT is, it works with non-linear complex variable. It performs better in the training stage than the testing stage because it has no overfitting problems. The probability is calculated by logarithm of ratio between known feature attribute values to the unknown feature attribute data set. it can be defined as:

$$P_n(d_i) = \sum_{n=1}^{N} \gamma_n dt_n(d_i) \tag{10}$$

Here $P_n(d_i)$ is the probability of attributes in the weather forecasting model and it is evaluated from the N. regression trees $dt_n(d_i)$ and γ_n is the step length. At each iteration of the process, a weak decision tree $dt(d_i)$ is selected to reduce the loss function $loss\ [y_i, P_n(d_i)]$. here y_i is a value of observing d_i. Now the equation is formed as,

$$P_n(d_i) = P_{n-1} dt_n(d_i) + \gamma_n dt_n(d_i) \tag{11}$$

$$P_n(d_i) = P_{n-1} dt_n(d_i) + \arg min \sum_{i=1}^{n} loss\left[y_i, P_{n-1}(d_i) - dt_n(d_i)\right] \tag{12}$$

The gradient loss function can be defined as residual error between y_i and P_{n-1}. $dt_n(d_i)$ is expressed as:

$$P_n(d_i) = P_{n-1}(d) + \gamma_n \sum_{i=1}^{n} \nabla loss\left[y_i, P_n(d_i)\right] \tag{13}$$

In all iteration, a new weak module is created with respect to the last module-based errors. The GBDT module trains the weather data and produces a better prediction with low noise of the data.

3.4.3 Naive Bayes Bernoulli (NBB)

To improve the accurate analysis of weather forecasting Naïve Bayes technique is implemented. This technique is based on the concept of occurrence probability. And also, it shows the accurate outcome using attribute of the weather dataset and it receives the primitive process. The Bayes theorem is used in the NBB model and is defined as shown below:

$$prob(X|Y) = \frac{Prob(Y|X)\, prob(X)}{Prob(Y)} \tag{14}$$

In Eq. (14), the probability of Y is the evidence and X is the hypothesis. Here X and Y are the events. For finding the probability of X's occasion, the Y's occasion is a valid one. Then Y's occasion is termed as proof. The probability of X is priori of X. Similarly, the probability of $prob(X|Y)$ is deduced by Y.

3.4.4 KNN

KNN algorithm can be used for both predictive problems and classification of weather forecasting. Its analysis the weather input vector values of prediction values and observation values to generate the new set of data points. In the prediction of the weather condition [20,21], it uses a series of input data with different nearest neighbour values. In the weather attribute missing attribute, values are evaluated based on the similarity of attributes by using distance function. This paper uses Euclidean distance of each data from weather input data vector by using the following equation:

$$Dist\,(p,q) = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \tag{15}$$

Here $P = \{p_1, p_2, \ldots, p_n\}$ and $Q = \{q_1\ , q_2\ , \ldots, q_n\}$. The purpose of using KNN algorithm is predicting both numerical and categorical attribute values of weather dataset, missing values can be easily identified and also correlated data also considered. Notice that it is time consuming in the analysis of Big-data process.

3.5 Ensemble Learning for the Prediction of Weather Forecasting (EBWF)

An Ensemble Learning technique is a meta-algorithm that combines several ML algorithmic results into one model of prediction in order to improve the prediction rate. In this research, ensemble learning is implemented for prediction of the weather forecasting based on Random Forest, Gradient Boosting Decision Tree, Naive Bayes Bernoulli, and KNN Algorithms. The prediction outcomes of this evolutionary algorithm are then ensemble using max voting to obtain the best final result. This bagging concept is implemented by the following algorithm:

$$f\,(x) = \frac{1}{m}\sum_{i=1}^{m} f_i\,(x) \tag{16}$$

Algorithm: 2

```
    Input: big weather dataset
    Output: Predictions using classifier
    Step 1: Pre-process: the weather input data set is pre-processed using the Section 3.2
    Step 2: Feature Selection: the pre-processed input for selecting the relevant features, given in Section 3.3 using the algorithm 1.
    Step 3: Ensemble Methods: selected input features are then given to prediction algorithms such as Random Forest, Gradient Boosting Decision Tree, Naive Bayes Bernoulli, KNN.
    Step 4: Ensemble Learning: Each algorithm outcome is calculated separately. The maximum prediction result is the final prediction result of the proposed method.
Max (output (RF), output (GBDT), output (NBB), output(KNN))
    Step 5: Output: return the prediction result.
```

4 Result and Discussion

4.1 Performance of Metric Measures for Performance Analysis

The proposed work provides the ensemble-based prediction of weather forecasting model using Random Forest, Gradient Boosting Decision Tree, Naive Bayes Bernoulli, and KNN Algorithm. For this we are using the following parametric metric measures:

Correlation Coefficient (CC)

It reflects the correlation between the attribute of weather forecasting and observation of attributes.

$$Corre = \frac{cov\left(A, Obs\right)}{\sqrt{Var\left(A\right)}\sqrt{Var\left(Obs\right)}} \tag{17}$$

Here, $cov\left(A, Obs\right)$ is the covariance outcome of weather forecasting model.

$Var\left(A\right)$ and $Var\left(Obs\right)$ is the variance of the weather forecast model and observation of attributes in the weather forecasting model.

$$cov\left(A, Obs\right) = \sum_{i=1}^{n}\left(A_i - \bar{A}\right)\left(Obs_i - \overline{Obs}\right) \tag{18}$$

$$Var\left(A\right) = \sum_{i=1}^{n}\left(A_i - \bar{A}\right)^2 \tag{19}$$

$$Var\left(Obs\right) = \sum_{i=1}^{n}\left(Obs_i - \overline{Obs}\right)^2 \tag{20}$$

Classification Error Rate or Misclassification (CER)

It is used to calculate as the fraction of predictions were incorrect.

$$CER = \left(1 - Accuracy\right) \tag{21}$$

Agreement Index

This is a measure of the prediction error in the weather forecasting model and it is calculated bas shown in the following formula:

$$Index - A = 1 - \frac{\sum_{i=1}^{n}\left(A_i - Obs_i\right)^2}{\sum_{i=1}^{n}\left(\left|A_i - \overline{obs}\right| + \left|Obs_i - \overline{Obs}\right|\right)^2}\ 0 \le Index - A \le 1 \tag{22}$$

The range of index agreement ($Index - A$) varies between 0 and 1; when the $Index - A$ value is close to 1, that refers to an exact matching outcome and 0 refers no agreement at all.

Nash-Sutcliffe Efficiency Coefficient (NSE)

It is used to access the prediction of weather forecasting model based on numerical values and it can be calculated by:

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(A_i - Obs_i\right)^2}{\sum_{i=1}^{n}\left(Obs_i\overline{Obs}\right)^2} \tag{23}$$

NSE ranges from $-\infty$ to 1. If the outcome of NSE is 1, that means it matches the observed attribute perfectly.

Prediction Time (PT)

It calculates the time required to predict the weather forecasting and it is calculated by using:

$$PT = n * time\ \left(EBWF\right) \tag{24}$$

Here, $time\ \ (EBWF)$ is the time taken for the prediction of weather forecasting algorithms like Random Forest, Gradient Boosting Decision Tree, Naive Bayes Bernoulli, and KNN Algorithms. time is evaluated in terms of ms. And n is the total number of big weather data in the dataset.

Multi-Class Confusion Matrix is used to represent the performance of a multi-class classification model in terms of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

Classification Accuracy

$$Classification\ accuracy = \frac{TP + TN}{TP + TN + FP + FN} X100 \tag{25}$$

It is used to calculate as the ratio between number of correct classifications to the total number of classifications.

Classification Precision

$$Classification\ precision = \frac{TP}{TP + FP} X100 \tag{26}$$

It is the ratio between correctly positive labelled classifier to the total number of all positive labels.

Classification Recall

$$Classification\ recall = \frac{TP}{TP + FN} \times 100 \tag{27}$$

$$F1 = \frac{2{*}precision{*}Recall}{Precision + Recall} \tag{28}$$

$$Specificity = \frac{TN}{TN + FP} \tag{29}$$

Tab. 3 show the comparison of Correlation coefficient (CC), Index Agreement (IA), and Nash-Sutcliffe Efficiency Coefficient (NSE).

Table 3: Comparison of CC, IA and NSE

Algorithm	CC	IA	NSE
RF	0.891	0.783	0.842
GBDT	0.916	0.894	0.906
NBB	0.919	0.904	0.911
KNN	0.883	0.771	0.832
Proposed ensembled (EBWF)	0.937	0.939	0.914

Tab. 3 shows that the proposed ensemble produced the better result compared with other existing algorithms. Fig. 5 show the calculation of classification error rate using Eq. (21).

Fig. 5 shows that the proposed ensemble-based algorithm produces minimum error rate of 0.043 in the CER train data. The classification error rate of train data set is random forest got 0.116, gradient boost decision tree 0.074, NBB 0.061 and KNN got 0.107. In the test data, ensemble-based algorithm produces minimum error rate of 0.051. The classification error rate of test data set is random forest got

0.121, gradient boost decision tree 0.082, NBB 0.066 and KNN got 0.109. Fig. 6 show the prediction time of various ML algorithms.

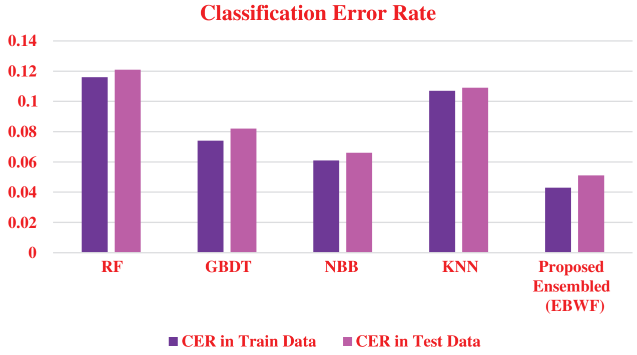


Figure 5: Classification error rate

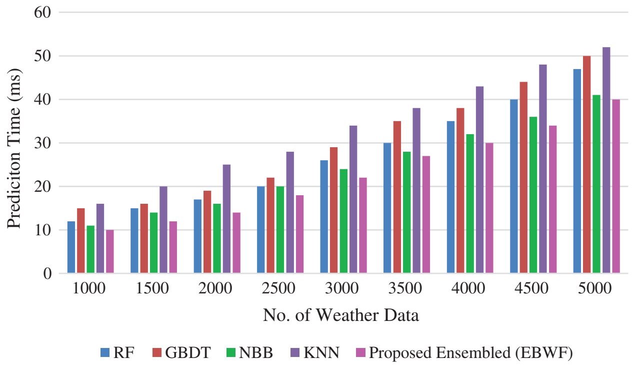


Figure 6: Prediction time

Fig. 6 shows that the prediction time of the bigdata of weather input is analysed. There are various sizes of the data in the weather dataset. Our proposed EBWF technique requires less time to predict the weather forecasting. Tab. 4 shows the accuracy rate of both training (80%) and testing (20%) data in the weather dataset.

Table 4: Accuracy rate in various algorithms

Algorithm	Accuracy in train data	Accuracy in test data
RF	0.884	0.879
GBDT	0.926	0.918
NBB	0.939	0.934
KNN	0.893	0.891
Proposed ensembled (EBWF)	0.957	0.949

In the Tab. 4, the results of various algorithms are compared based on Accuracy parametric measures in both training and testing dataset. The proposed ensembled based (EBWF) got 0.957 accuracy rate in the training data set and similarly for the testing dataset 0.949 accuracy rate. It gives better accuracy rate when comparing it with various algorithms. Tab. 5 shows the precision and recall rate of various algorithms.

Table 5: Precision, recall, specificity

Algorithm	Precision	Recall	Specificity
RF	0.7867	0.6891	0.6734
GBDT	0.8911	0.9011	0.8923
NBB	0.9393	0.9347	0.9211
KNN	0.6156	0.6421	0.6377
Proposed ensembled (EBWF)	0.9578	0.9492	0.9366

In Tab. 5, the results of various algorithms are compared based on precision and recall parametric measures. The proposed ensembled based (EBWF) model got 0.9681 precision, 0.9592 recall, and 0.9366 specificity. Fig. 7 shows the F1-score metric rate of various algorithms.

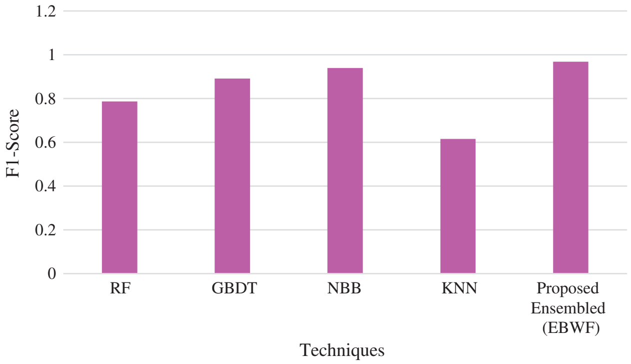


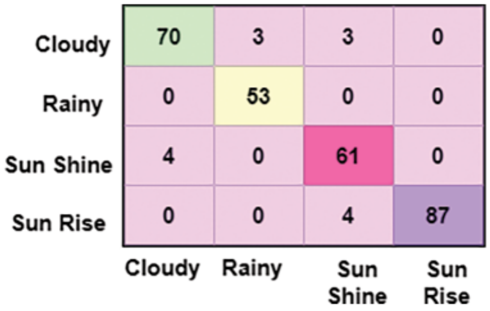
Figure 7: F1-Score

Fig. 7 shows the comparison of F1-Score with various algorithms. The results show that our proposed work outperforms other methods. The performance of the proposed ensemble model with the proposed EBWF framework shows is better in terms of high accuracy, less error, and less prediction time. In this research, ensemble learning is implemented for prediction of the weather forecasting based on Random Forest, Gradient Boosting Decision Tree, Naive Bayes Bernoulli, and KNN Algorithms. Each algorithm outcome is calculated separately.

Max (output (RF), output (GBDT), output (NBB), output(KNN))

The prediction outcomes of this evolutionary algorithm are then ensemble using max voting to obtain the best final result. Fig. 8 shows that classifier performance of confusion matrix for the test data set with classes of {*Cloudy*, *Rainy*, *Sun shine*, *Sun rise*} with factors of confusion terms are TP, TN, FP, FN.

In the Fig. 8 describes that confusion matrix of testing data in the data set with the classifiers of cloudy, rainy, sun shine and sun rise for the ensemble based proposed work.



	Cloudy	Rainy	Sun Shine	Sun Rise
Cloudy	70	3	3	0
Rainy	0	53	0	0
Sun Shine	4	0	61	0
Sun Rise	0	0	4	87

Figure 8: Confusion matrix of test data PWFM

5 Conclusion

In this proposed work, ensemble model is compared with existing machine learning algorithms for predicting weather using essential performance measures. We have observed that ensemble based EBWF prediction system gives the best weather prediction results. The aim of this proposed work is to have high accuracy rate, low error, and less prediction time. For the evaluation purpose, we used airport weather data gathered from different stations in India. This research helps various communities like fishing, transport, farming etc. In fishing it alert population regarding weather condition. In farming it helps to plan plantations and irrigation. The results of the proposed EBWF model outperform other techniques which are Random Forest, KNN, GBDT, and NBB. The ensemble-based EBWF model resulted with 0.957 accuracy rates using the training data set and similarly 0.949 accuracy rate for the testing dataset. In our future work, research will explore by connecting IoT devices for collecting weather data which can help produce high accuracy in less perdition time and improve the decision-making process.

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