Short Term Weather Forecasting Comparison Based on Machine Learning Algorithms

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***Abstract*—Forecasting is the term used to describe the attempt to predict outcomes in unknown or uncertain situations. The most vital factor in many applications of weather forecasting is air temperature. The air temperature alone can't be the effecting point of forecasting weather. Moreover, with the advancement of computer technologies, forecasting models have been transformed widely. This paper approached a system that forecasts air temperature using machine learning algorithms. Several regression methods were employed to attempt to predict temperatures. This research evaluated four algorithms (Decision Tree, AdaBoost, Random Forest, and Gradient Boosting) on some meteorological data over three years (2015-2019), where 80 percent of the total data set was utilized for training and tested on 20 percent. The variables used include Wind speed, Relative Humidity, Dew point, and Air pressure. The objective was to determine which regressor achieves better outcomes for forecasting air temperature with the lowest error rate. This research concluded that the Random Forest Regressor is the most accurate in prediction. Here, MAE is used to determine the accuracy. On average, the Random forest had the lowest MAE value of 0.102, which was lower than the outcomes of the other three algorithms.**

***Index Terms*—Data mining, forecasting, machine learning**

I. Introduction

Since the early 1990s, a lot of research has been done on how science and technology can be used to predict the climate in a certain place. Weather forecasting means using scientific and technological methods to anticipate the atmospheric conditions for a particular place. Then atmospheric scientists viewed weather forecasting as a congenitally deterministic enterprise. The case of forecasting, especially weather forecasting, grabbed a lot of attention from researchers, scientists, and mass people. Weather forecasting is a process of anticipating weather using some input data which were previously observed [1]. The forecasting domain has transformed its shape gradually in the late 90s of the last century. Weather forecasting may be the foremost reason that integrates meteorology with Computer Science as a research domain. In the past, this was accomplished through the labor of humans, but with the implementation of computers, the process has become much easier. Numerical Weather Prediction (NWP) was the first step, which involved using equations of motion to predict the weather in the future with accurate starting conditions. Now, Machine Learning techniques are being utilized to further enhance forecasting, allowing for the analysis of vast amounts of machine-generated forecasts. Machine Learning is resilient in the face of changes and does not require any other variables to make predictions [2]. Therefore, machine learning is relatively better approach to propagate weather forecasting domain. Prior to the substantial progress in technology, predicting the weather was a very difficult challenge. Weather forecasters used satellites and data models to estimate atmospheric conditions, but with limited precision. In the past few decades, the introduction of the Internet of Things has greatly increased the accuracy and predictability of weather forecasting and analysis.

Data Science and Artificial Intelligence have enabled scientists to make highly accurate and predictable meteorological forecasts [3]. In 2016, it was shown that an Amazon ML model could be reconstructed with almost perfect accuracy by collecting responses to a few thousand queries. This suggests that attackers could use publicly available algorithms to gather training and threat data, and then develop new attacks that appear ordinary to ML-based assessments. The climate of a certain area is determined by the variations in atmospheric pressure, temperature, and humidity between it and other regions [4]. In this paper we try to examine different machine learning algorithms which works better on our collected dataset. Weather predictions are generated by gathering quantitative information about the present and past conditions of the ambience [5]. The weather forecasting plays a pivotal role in protecting the life and property in different adverse scenarios. Weather forecasting has been more adapted due its wide range of implementations from the irrigation to the airspace [6]. Forecasts can be divided into four categories: daily-range, short-range, medium-range, and extended-range. Daily-range forecasts cover up to 12 hours in the future, while short-range forecasts cover 1 to 2 days. Medium-range forecasts are valid for three to seven days, and extended-range forecasts cover more than a week. Numerical forecasting techniques are most successful for short-range forecasts.

The paper has been arranged in this way. In Section II, related works on weather forecasting are discussed. In Section III, discussion of the research method and applied Regressors is explained. At the following section, Section IV, proposed system is analyzed from the resulted temperatures with relevant graph and tables. Moreover, the implemented models are compared by error detection formula. The system's future work is discussed in Section V, which also contains the research's conclusions.

II. Related Works

Weather forecasting has seen a variety of approaches in recent years based on different neural networks and machine learning algorithms.

A data-driven model for weather forecasting was developed by considering the temporal modeling techniques of long short-term memory and temporal convolutional networks in [7]. These models were compared to various classical machine learning, statistical forecasting, and dynamic ensemble methods, as well as the established numerical weather prediction (NWP) WRF model. They used SR, SVR, and RF as the classical machine learning approaches. ARIMA, VAR, and VECM were the statistical forecasting approaches, and AFE was the dynamic ensemble method in their model. The model captured weather information through time-series data and assessed two different regressions, multi-input multi-output and multi-input single-output, using LSTM and TCN layers. Chauhan and Thakar [8] implemented neural network-based weather forecasting, which was about climate determination. This implementation focused on a transfer function-based approach to minimize the error in forecasting.

Rasp et al. demonstrated that data-driven techniques such as deep learning can be used effectively to make predictions in many domains [9]. They proposed a benchmark data set to assess the potential of these methods to assume global weather patterns a few days in advance and provided ERA5-sourced data and clear evaluation metrics that could be used to compare different approaches. Furthermore, they came up with baseline results from linear regression, deep learning, and physical forecasting models.

Hess and Bores [10] demonstrated that deep learning could improve NWP models' accuracy in predicting heavy rainfall events. The proposed post-processing approach effectively corrected errors in the model-predicted rainfall. Based on the event size, it increased the forecasting accuracy of extreme rainfall events by a factor of two to above six. This technique may prove especially useful in areas with variable weather patterns and intense rainfall, where traditional NWP models struggle to predict extreme events accurately.

Another artificial neural network-based work was done by Feghi et al. [11], where they developed a function approximator to determine the air temperature. This work focused on evaluating the air temperature using an efficient ANN-based model through a function. Radial Basis Function (RBF) was utilized as a notable architecture of neural networks for function approximation, described in [12]. Different supervised and unsupervised algorithms train the RBF networks. This model was developed using meteorological data collected over one year and then tested with data from a different year. When the number of hidden layers reached 49, the accuracy was lower.

In an investigative ANN-based model, Seyyedabbasi et al. [13] predicted the general weather conditions (such as temperature, humidity, perception, and wind). The motive was to identify the dependency between social activities and weather conditions. More neurons could have substantially improved the performance of the model. It has been well-established that to evaluate and describe the atmosphere without error or with minimal errors needs massive computational power [14]. One such robust implementation was made to address this issue. And also successfully improved the prediction rate for weather data. However, the weather forecasting model or domain is one of the most versatile domains, as each location's conditions, data, and atmosphere vary. Therefore, users and predictors been argued about the 'goodness' of forecasting [15]. The apparent gap existed due to the viewpoints of both parties. Moreover, the difference between 'quality' and 'consistency' was also a disagreement.

In this paper, we focused on machine learning to forecast numerical short term weather prediction [16]. After some necessary analysis, we developed four machine learning algorithms that applied to the data set, as these four algorithms are most popular in predicting weather conditions. For predictive models, tree-based methods [17] come up with high accuracy and solidity and boost the clarification of results. In boosting algorithm [18], the learners focus on the error of the previous learner rather than predicting the purposive outcome to train the weak learners [19]. We have also examined which algorithm works better by calculating MSE and MAPE.

III. Research Method

The following acts have been taken to predict the weather temperature:

1) Collection of Data
2) Preparing the Data
3) Trained the models to predict

The workflow of this research work is visualized in "Fig. 1".

A. Collection of Data

In this research work, the weather data have been collected from historical weather of the wunderground from 2015 to July 2019 [20]. The data represent the weather pattern of Dhaka city (GMT +6.00). In total, there were 1632 records of weather parameters in this dataset. The data from January 2015 through December 2018 are for training Regressors, while the data from 2019 are for testing Regressors. The data set has four input variables with min and max values and one output variable. The inputs used for temperature forecasting include four parameters: Wind speed, relative humidity, dew point, and air pressure. Due to their effect on air temperature, these weather parameters have been selected. The weather parameter for this work is given in Table I.

B. Preparing the Data

The preparation of data was a crucial part of the whole work. After collecting the data, we formatted the data to make it stable for forecasting. First, the day, month, and year are

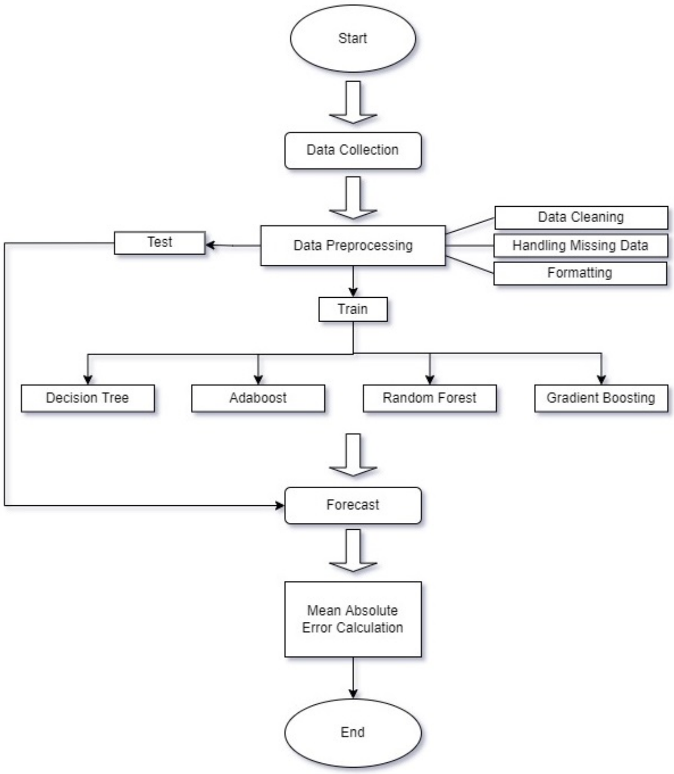

Fig. 1. Methodology of this work

separated from the data to create an individual property. We omitted the year column to reduce the data size because this parameter does not affect the prediction. Moreover, in some parameters, the value was given as min and max, which was further converted into one column by averaging those two values. The snapshot of the initial data set is in "Fig. 2". Finally, the .xls file is converted to .csv format to predict the temperature. There are 1633 rows in our collected dataset.

No	Day	Month	Dew PointMax	Dew PointMin	Dew PointAvg	Hum-dityMax	Hum-dityMin	Wind SpeedMax	Wind SpeedMin	Pre-ssureMax	Pre-ssureMin	Temp-erature
1	1	1	72	63	55	60	94	44	7	0	29.98	29.89
2	2	1	100	64	52	61	83	11	6	0	30.01	29.89
3	3	1	76	68	59	63	83	45	7	0	29.98	29.86
4	4	1	74	68	61	65	88	54	12	0	29.95	29.83
5	5	1	70	64	54	59	88	44	12	0	29.95	29.83
6	6	1	68	57	46	53	82	38	12	0	29.98	29.86
7	7	1	66	61	46	54	94	41	9	0	29.98	29.89
8	8	1	66	63	50	55	94	44	9	0	29.98	29.86
9	9	1	67	64	52	57	94	53	7	0	29.98	29.86
10	10	1	66	59	52	56	94	47	8	0	30.04	29.92
11	11	1	63	57	46	53	94	43	9	0	30.06	29.95
12	12	1	65	57	50	53	94	41	9	0	30.04	29.92
13	13	1	65	63	54	57	100	44	7	0	30.04	29.86
14	14	1	70	64	55	60	94	51	7	0	30.01	29.89
15	15	1	70	64	54	58	94	39	9	0	30.01	29.89
16	16	1	72	57	50	55	88	30	7	0	30.01	29.89
17	17	1	68	63	55	59	94	61	17	0	29.98	29.89
18	18	1	60	59	55	56	94	77	12	0	30.04	29.92
19	19	1	60	61	54	56	94	82	9	0	30.04	29.95
20	20	1	62	55	52	54	88	68	8	0	30.09	30.01
21	21	1	64	59	54	56	100	57	7	0	30.15	30.01
22	22	1	67	64	48	57	94	36	9	0	30.09	29.98
23	23	1	70	64	55	58	94	42	9	0	30.01	29.89
24	24	1	71	59	52	56	82	42	7	0	30.04	29.92
25	25	1	70	61	50	56	83	36	12	0	30.09	29.98
26	26	1	68	59	48	54	88	34	12	0	30.06	29.95
27	27	1	69	61	48	55	82	36	13	0	30.01	29.89
28	28	1	71	61	54	57	83	39	12	0	29.98	29.89
..	..	..	..	..	..	..	..	..	..	..	..	..
1633	31	2	8	59	55	58	83	53	14	0	30.04	29.92

Fig. 2. Snapshot of initial data set for Weather Forecasting

TABLE I
METEROLOGICAL VARIABLES

No	Variable taken everyday	Unit
1	Wind Speed	mph
2	Relative humidity	%
3	Dew point	F°
4	Air Pressure	hg
5	Temperature	F°

C. Trained the models to predict

We have used different machine learning techniques [21] for weather forecasting. In this work, we have developed a forecaster which can predict temperature, but these four algorithms have other applications also.

1) Decision tree Regressor: The Decision Tree can classify, identify, or predict values from a given data set. It is a predictive modeling technique that builds a model of an input data set to indicate the output values of new data. The decision tree makes a series of decisions or splits into the data set to identify which data groups have similar characteristics. The decision tree algorithm makes decisions based on entropy and information gain. Entropy measures the amount of disorder or randomness in a data set. Information gain measures how much knowledge is gained from making a decision. The decision tree algorithm determines the best split of a given data set based on these two measures. The decision tree solves both classification and regression problems. It is commonly used in machine learning applications such as image and voice recognition and in data mining [22]. The performance of the Decision Tree is calculated based on accuracy, precision, recall, F1-score, and other metrics. It helps to identify the best set of hyperparameters and to determine the best feature set in the Decision Tree.

2) AdaBoost Regressor: The main advantages of Boosting algorithms are that they are simple to implement, require lesser data pre-processing, and have excellent accuracy. They are also fast and require less memory. Furthermore, They can handle data with many features and are suitable for datasets with large amounts of noise [23]. Boosting algorithms can also be used to ensemble multiple models together, which can further increase the accuracy of the model [24]. Finally, Boosting algorithms are relatively robust to outliers. 'Boosting' depicts an algorithm where weak learners are converted into strong ones. It makes 'n' numbers of trees during the training period of data [25].

3) Random Forest Regressor: Random forest is also one of the most prominent algorithms due to its simplicity and versatility. Classification and regression analyses are two of the applications that can benefit from its use. [26]. We have applied this algorithm for classification tasks on the train data. In the first stage, a random forest is created by randomly selecting a set of features from the training dataset. Random Forest generates 'n' no of decision trees to calculate the output. This process repeats multiple times, and a new decision tree is built each time with different randomly selected features.

Each decision tree will produce a prediction, and the class with the most votes is chosen as the final prediction as shown in "Fig. 2". As it takes from multiple decision trees,

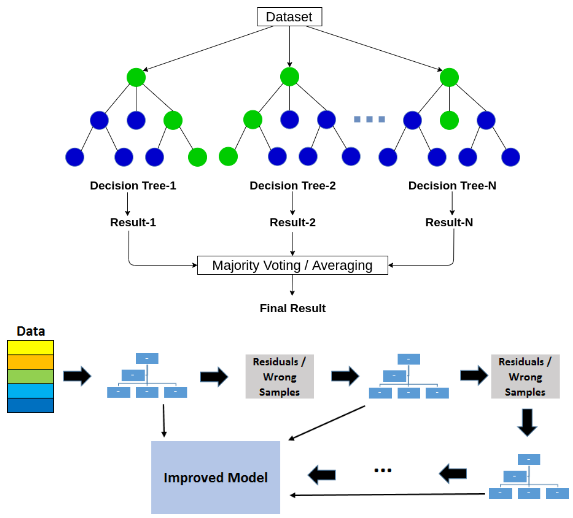

Fig. 3. Working procedure of tree and boosting based Regressors [27]

it selects the prediction result with the most votes as the final prediction from the input data, so it gives pretty good results on forecasting [28].

4) Gradient boosting Regressor: Gradient boosting is another boosting algorithm that builds a robust model by iterative process and minimizes the loss function when the algorithm goes towards a negative gradient. "Gradient" means when there is more than one derivative of the same position. It relies on the fact that the best possible next model is created when combined with previous models and also minimizes the overall prediction error, as illustrated in "Fig. 2" [29]. This idea is applied in this work to set the [30] target outcomes for this next model to minimize the error in the prediction of weather temperature. The loss function explicitly helps predict the accuracy of a specific output of any forcasters [31]. However, Gradiet Boosting can be computationally expensive, especially when large data sets are involved. Additionally, it can be prone to overfitting if the number of trees is too high.

Gradient boosting and the AdaBoost Regressor are reasonably identical, but there is one distinction: Adaboost tackles weak models by updating the weights of the weak ones. However, Gradient Boosting focuses on the loss function to determine how many mistakes are still in the forecast temperature.

IV. Result and Discussion

We started with input data representing the four main variables in Table I. A sample of the output of the four Regressors has shown in Table II. We have also tried to visualize the difference among the implemented models.

The data has been divided into two parts training and testing. 80% of the total data is used as a train set and then left 20% used as a test set. First, the train set has used to fit

TABLE II
The output of the last one month using Decision Tree, AdaBoost, Random Forest, and Gradient Boosting Regressor

Actual	Decision tree	AdaBoost	Random Forest	Gradient Boosting
88	88	86	86	84
88	83	86	82	82
89	86	86	86	86
90	73	68	74	76
88	84	86	84	84
85	74	68	71	69
84	72	68	71	73
86	84	86	86	84
84	73	68	76	76
82	82	68	85	86
86	86	86	87	88
80	84	86	87	80
80	83	86	83	80
86	89	86	88	86
88	84	86	86	84
88	74	68	71	69
88	83	86	86	86
88	86	86	90	88
90	86	86	86	86
90	84	86	84	82
90	78	68	78	78
90	71	68	71	71
86	72	68	72	74
81	71	68	71	71
82	89	86	86	86
81	74	86	84	80
83	82	86	80	78
84	84	86	84	84
86	80	86	82	80
86	82	86	82	82
84	74	68	75	75

the four implemented models, and then the models predict the weather temperature on the test set. We first train the four models with the input data every time we have got different values. Table II shows the actual values of our dataset from last month(July) after the third iteration. The tree-based regressor, Random Forest, produces better results than the other three models. The average actual value is 85.839, whereas the average predicted value of Random Forest is 81.097. However, the AdaBoost regressor's result is quite far from the true value of 79.613. Decision tree and Gradient Boosting give almost similar results. We have also made a comparison graph to observe the overall performance of these four implemented models.

In "Fig. 4", we have shown the graphical representation of the output of the four Regressors. There is no fixed rule on which Regressor works best on the input data, but in this research, the random forest gives the highest accuracy with minimum error. In the previous works, Random forest gave a minimum mistake than the other algorithms. [32] Because Random Forest Regressor creates multiple decision trees and takes the positive voting from that decision tree. The Decision Tree also gives less error in predicting the temperature. In this work, we have used this algorithm to predict the daily weather temperature. In some papers, to expect fog, rain, and thunder probability, the decision tree algorithm is applied to help people plan their outdoor activities [20]. Previously Adaboost [25] was applied for forecasting the wind speed, but in this work, we have tried to use it as a weather forecaster though it doesn't work well on temperature forecasting. In "Fig. 4", it clearly can't reach the actual temperature level.

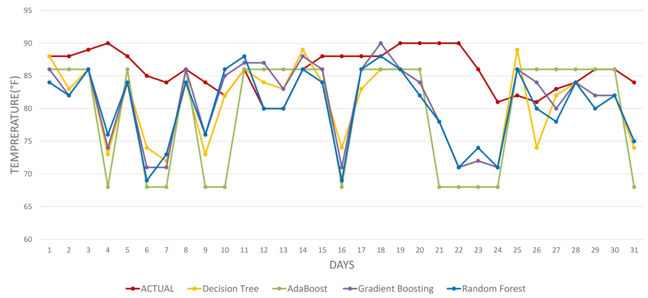

Fig. 4. Actual and Predicted values of four Regressors

Gradient boosting algorithm was applied in fields like the solar system, evapotranspiration with meteorological data, and weather forecasting. In this work, this algorithm has been used as a weather forecaster, and from Table III, we can conclude that Gradient boosting also works quite well on weather data.

TABLE III
MAE VALUES OF DECISION TREE, ADABOOST, RANDOM FOREST AND GRADIENT BOOSTING REGRESSOR OF 10 TESTS

No. of Test	MAE of DT	MAE of AB	MAE of RB	MAE of GB
TEST 1	0.103	0.116	0.102	0.103
TEST 2	0.104	0.116	0.104	0.103
TEST 3	0.103	0.116	0.103	0.103
TEST 4	0.104	0.116	0.099	0.104
TEST 5	0.103	0.116	0.102	0.103
TEST 5	0.102	0.116	0.103	0.102
TEST 6	0.103	0.116	0.102	0.103
TEST 7	0.104	0.116	0.100	0.103
TEST 8	0.105	0.116	0.102	0.103
TEST 9	0.103	0.116	0.104	0.104
TEST10	0.103	0.116	0.102	0.103
Avg	0.103	0.116	**0.102**	0.103
Max	0.105	0.116	0.104	0.104

In the "Fig. 4", it is illustrated that all Regressors used in this research paper always underestimate the actual value of the weather, and the Random Forest Regressor generates a similar value compared with the true value. To evaluate their performance the models are tested ten times. In each run, they develop different values. From "Fig. 4", we can determine that all the temperature values are between 67 and 90 approximately. Moreover, on day 1, the Decision tree forecasts the exact value of the actual temperature. In the period from day 18 to 21, temperature holds a similar value, and at this point of the graph, no regressor can predict the desired output. After that, error detection techniques are applied to these four models' actual and expected values to measure the accuracy or performance. Among all types of error detection formula of Mean Absolute Error is used. MAE helps to differentiate the Regressors in this research work. Table III shows the summary of MAE, where the lowest value of MAE is 0.102, which the Random Forest Regressor acquired. The Mean Absolute Error (MAE) measures the average magnitude of the errors in a set of predictions without considering their direction. It measures the average of the absolute errors between predicted and actual values. The MAE is a linear score, meaning that all individual differences are weighted equally in the standard.

In "Fig. 5", it is shown that all the values of Mean Absolute Error are fall under o to around 0.24. The range of the error's

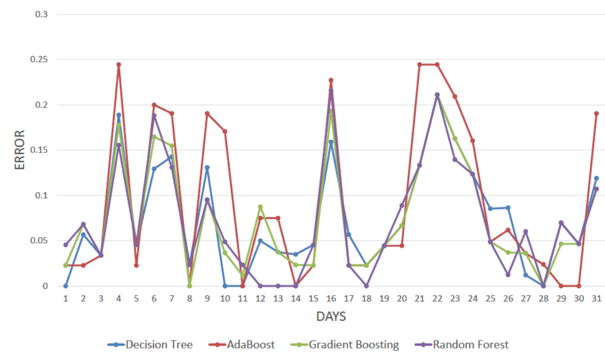

Fig. 5. The value of Mean Absolute Error of the four Regressors

maximum values is 0 to 0.15. At some point, the MAE value is equal to zero. The most significant error values are between 0.15 and 0.25. AdaBoost Regressor yields a maximum error of about 0.22. Here the graph shows Random Forest has a minimum MAE value. Due to their relative error values, the decision tree and gradient-boosting Regressors produce comparable results. It is typical to see some abnormalities in the outcomes from the actual values. A Regressor or algorithm that is error-free cannot exist.

V. Conclusion and Future Work

We've provided an approach of four distinct regressors for predicting air temperature based on meteorological data. The algorithms are trained on the used dataset upon several iterations. Following that, the remaining 20% dataset then utilizes for testing. Here the regressors are tested ten times to observe the changes. According to the experimental findings of the last month of the dataset, the Random Forest Regressor performs better on the data with good accuracy and a lower MAE value. In contrast, Adaboost can't forecast the desired output. So, the prediction of weather temperature can be made using the Random Forest Regressor. Boosting algorithms could perform better on our dataset. In the future, we are planning to add some more features to this work as developing better forecasting techniques for extreme weather events like thunderstorms, hurricanes, and tornadoes, utilizing new data sources such as satellite imagery, drones, and citizen science networks to enhance weather forecasting, improving the accuracy and reliability of numerical weather prediction models, Utilizing big data and artificial intelligence to improve weather forecasting, researching ways to use weather forecasting to improve aviation safety and reduce delays. Moreover, we will compare recent works with our implemented model and test the performance of these four algorithms with different datasets to evaluate how well they perform.

VI. Limitations

In this work, the graphs and forecasted temperatures indicate that the estimated values do not match the real ones. The issue of under-fitting persists. Using a threshold approach can help to address this problem. To boost the value of anticipated values, upper and lower criteria are used. Moreover, collecting real-time data was the main challenge. We altered weather temperature data to a usable form. Thus, the data set needs to be vaster. An expanded data set will allow the models to work with additional weather pattern values, enhancing their accuracy.

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