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Analysis of PCA based AdaBoost Machine Learning Model for Predict Mid-Term Weather Forecasting

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Abstract

In general, weather forecasting is done with the use of enormously complicated physical science models that use a variety of environmental circumstances over a long period of time. Because of the annoyances of the climatic framework, these criteria are frequently fragile, causing the models to produce inaccurate forecasts. The models are mostly run on multiple hubs in a massive High-Performance Computing (HPC) environment that uses a lot of energy. In this research, we offer a climate expectation approach that uses historical data from various climate stations to create basic AI models that may provide meaningful forecasts for specific climatic conditions in the not-too-distant future within a given time frame. In this paper, we offer a climate expectation approach that uses historical data from several climate stations to create basic AI models that can anticipate certain climatic conditions in the not-too-distant future within a given time frame. Overall research performed into two stages; in first stage Principle component Analysis has been used to extract the irrelevant attributes from the datasets. In second stage five different machines learning algorithm used to predict temperature condition for midterm span & finally four performance indicators along with training time used to identify the best fitted model. From the result analysis it is seen that PCA based AdaBoost model is the fittest model with acquired the best outcome of R2, RMSE, MAE & MSE are 0.992, 0.539, 0.398 & 0.209 respectively. Beside of this present model also outperformed than the other state of art model proposed for midterm weather forecasting purpose.

Keywords

Machine learning, PCA, Performance indicator, Weather Forecasting.

INTRODUCTION

Since the start of mankind's set of experiences, individuals have consistently endeavored to foresee and comprehend the world, and the capacity to improve forecasts enjoys given serious benefits in assorted settings, like climate. Climate conditions all throughout the planet change quickly and continuously ([33], 2020). Right conjectures are fundamental in present-day by day life. From horticulture to industry, from going to everyday driving, we are subject to climate conjectures intensely. As the whole world is experiencing persistent environmental change and its incidental effects, foresee the climate with no mistake to guarantee simple and consistent versatility, just as protected everyday activities.

Climate forecasting is the rational prediction of environmental factors such as temperature, humidity, dew point, precipitation, and wind speed based on reliable data ([31], 2021). To acquire data for climate forecasts, barometers, radar, and thermometers are used ([19], 2020). In calculating climate, external variables such as present climate conditions, historical climate data, tracking the movement of air and mists in the sky, and detecting and verifying changes in gaseous tension are critical.

Exact climate estimating data is significant in guarding individuals and property against the dangers of nature. Business, tourism, sports, and agriculture, as well as mining, power, the food industry, airports, and naval architecture, all rely heavily on exact climate forecasting. In horticulture, earlier data about climate assists ranchers with taking fundamental choices to further develop their harvest yields. Air terminal or maritime frameworks require consistent climate information to know whether there is an unexpected change in climatic conditions ([3], 2017). Mining businesses require exact climate data to screen the Earth's covering consistently. Climate anticipating on every day, week by week, month to month, or yearly premise gets fundamental as it can more readily mirror the changing pattern of the environment and furthermore give convenient and effective ecological data for the choices at the miniature administration level ([17], 2017).

The quick improvement of advances like the IoT, WSN, Data mining, and Cloud Computing has assisted climate estimating with entering the period of Big Data ([20], 2017). Large information advances help to anticipate the future environment states all the more definitely. In addition, with the progression of AI procedures and proficient guideline part examination, climate determining and environment expectation can be made all the more adequately and precisely. In AI, we use several types of calculations to enable machines to learn how to connect the dots in the information provided and to determine the outcome. We employ several types of algorithms in machine learning to allow machines to learn the correlations within the data presented and generate predictions based on them. A Machine Learning Regression analysis includes simple computations that aid in establishing a link between a single dependent variable and multiple independent variables ([5], 2021). A few climate forecasting models based on machine learning have been presented in order to predict the climate with great accuracy.

Objective of the Research

Objective of the present research are following:

(1) The usage of AI in the forecast of climate conditions in mid timeframes

(2) Implementation of principle component analysis to extract the irrelevant attributes from the actual datasets.

(3) Goodness of fitted model predict with the help of statistical performance indicator.

(4) Finally a comparative study has been performed between proposed models with other state of art techniques.

The remainder of this paper is coordinated as follows: Section 2 gives an outline of AI in climate determining, just as the connection works. In Section 3, we present the philosophy of the proposed model incorporates with strategies to pull information from a climate followed by regression model. Section 4; describe the outcomes of the proposed model with the help of performance indicator & comparative study with state of art methods. Finally section 5 describes the conclusions & future scope of the present research.

RELATED WORK

In this section some of literature survey has been presented for weather forecasting using different artificial intelligence model. Two different regression models were proposed to forecast different time span of 1 year's weather forecasting datasets ([18], 2016). A hybrid Global climate model was proposed for weather forecasting offered better accuracy & less computational time than conventional neural network model that used neural networks([21], 2006). Two different model SVM & BP-ANN are proposed to forecast the 6 month weather. To design this model 5 years data was used to train & from the experimental result it is seen that SVM outperformed than BP-ANN ([32], 2009). A k-means cluster along with Hidden Markov predictive Model was used to identify the fluctuating patterns of weather conditions as well as upcoming weather conditions([41], 2016).

Various supervised & unsupervised data mining techniques were reviewed for different time span of weather forecasting model([23], 2018). To foresee the air parameters, weather prediction & numerical weather prediction was done by different machine learning algorithms ([24], 2019). An improved wavelet transform based feed forward neural network model studied for rainfall prediction. Proposed model also verified against other numerical predictive model for same datasets([39], 2019). A new weather prediction model was proposed by using machine learning algorithm through which most influential input parameter of the wind flow can be identified ([1], 2015). A comparative study was performed on the basis of short term wind flow forecasting using three different algorithms: ARIMA, ANN, and polynomial curve fitting ([38], 2011). Four different statistical algorithms: ANN, ARIMA, curve fitting & extrapolation with periodic functions were used to predict the wind speed corresponding to minimum number of input parameters. From the result analysis it is concluded that ANN & extrapolation with periodic functions performed better than other two algorithms ([22], 2008). An ensemble based (performed in pre processing stage) neural network model was proposed to predict temperature in Germany([34], 2018). The proposed structure is an alternate methodology for studying the current climate forecasting models, where climate estimating models are characterized essentially dependent on the procedure utilized.

METHODOLOGY

The general weather prediction framework shown in Figure 1 includes data pre-processing, model selection and evaluation. Due to advance technologies data can be collected through IoT, Wireless Sensor Networks (WSN), and Cloud Computing ([4], 2010; [17], 2017; [41], 2016). Once the data is collected may contain relevant & irrelevant information. In pre-process stage principle component analysis (PCA) used to eliminate the irrelevant information from the dataset to convert the unstructured dataset into structured one for make it better accuracy. Afterwards the structured datasets split into train & test dataset in a ratio of 4:1.

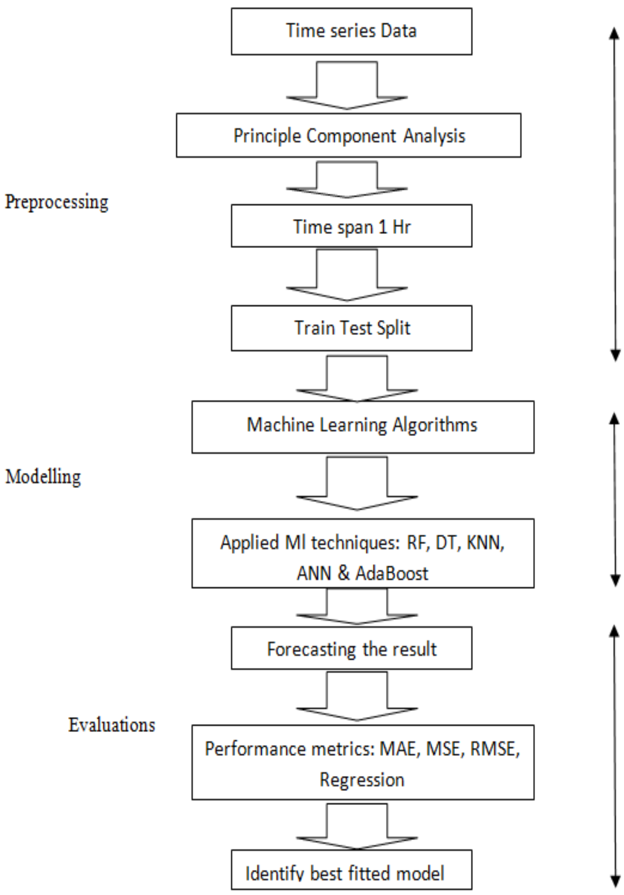

Figure 1. Flowchart for Proposed model

In the second stage, any forecasting system must choose a model and a training dataset. In this research we used five machine learning algorithm as forecasting model describe on later on section. During the training of each model proper parameter setting is done. To find the best-fit model, various statistical performance indicators such as MAE, RMSE, MSE, and R2 are used. Finally, the data are graphically represented using Scatter plots.

Dataset

Table 1. Datasets Information for the present model

Si No	Name of the attributes	Types	Role
1	Time	Date time	Feature
2	Local Time	Date time	Meta
3	Temperature	Numeric	Target
4	Precipitation	Numeric	Feature
5	Snowfall	Categorical	Feature
6	Snowmass	Categorical	Feature
7	Air density	Numeric	Feature
8	Radiation surface	Numeric	Feature
9	Cloud cover	Numeric	Feature

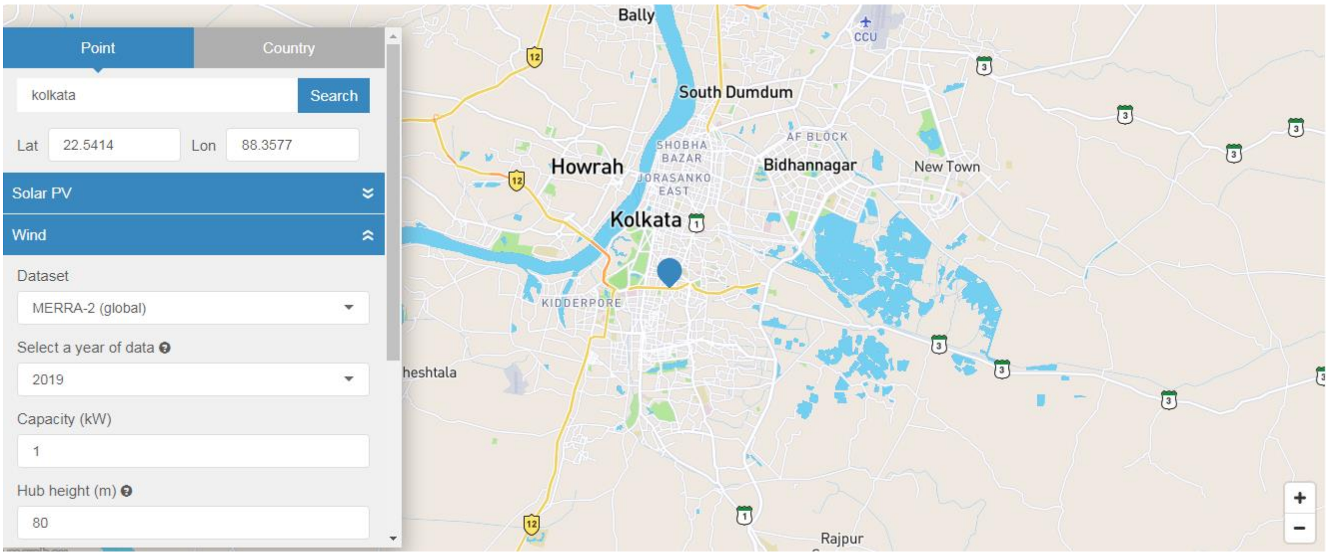

Figure 2. Google map for showing city & its surrounding places

Figure2 representing geographical position of Kolkata & its surrounding from where the experimental datasets of weather forecasting is taken. In this datasets Temperature is considered as a target variable. In this datasets containing the information from 1st January, 2019 to 31st December, 2019. In contrast, the test set contains 60 days of data starting from November 1, 2019 and ending on December 31, 2019. In this investigation, AI techniques are created dependent on the past upsides of estimated temperature information. Because of the nonlinear, non-fixed traits and the stochastic varieties in the weather time series, the precise expectation of temperature is known to be a difficult exertion ([35], 2019). In this work, to work on the precision of the temperature model, an examination between five models is directed to figure wind speed thinking about accessible chronicled information (https://www.renewables.ninja/). Qualities of the gathered information in 1 hour of the interval of time. Dataset contain 8760 rows with seven attributes. For testing purpose we consider 876 numbers of data.

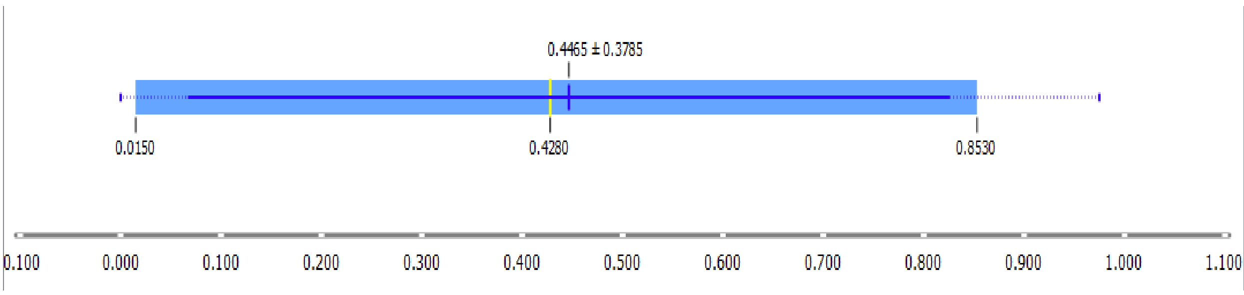

Figure 3. Box plot for Cloud cover

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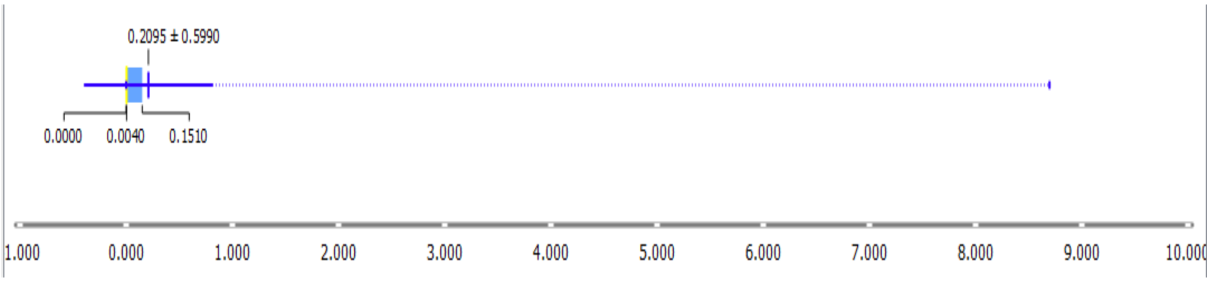

Figure 4. Box plot for precipitation

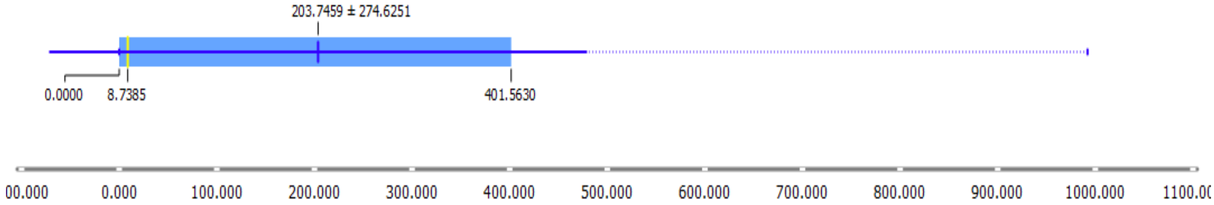

Figure 5. Box plot for surface radiation

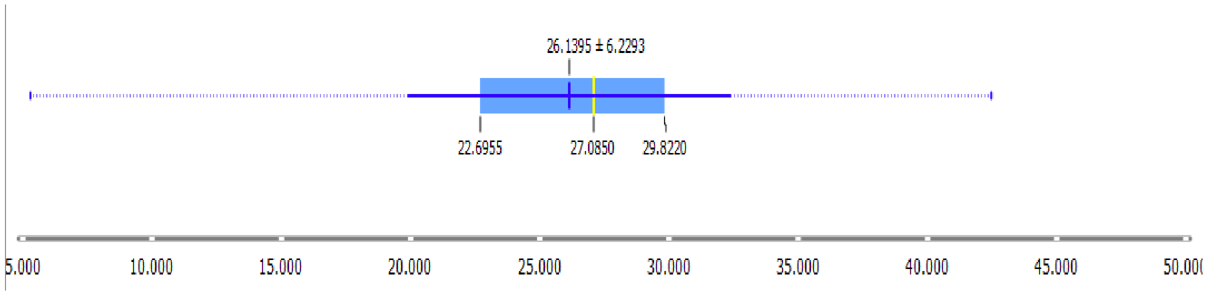

Figure 6. Box plot for Temperature

Figure 3 to Figure 6 representing the Box plot for the higher priority attributes: Cloud cover, precipitation & surface radiation respectively while Figure 5 represent the Box plot for temperature, output attributes of the datasets. In Table 1 describes the name, nature & role of the attributes in the present model are described.

Principal Component Analysis (PCA)

PCA is an unsupervised Feature Reduction approach for converting irrelevant datasets to low-dimensional data with the least amount of error. PCA is a statistically rigorous method for simplifying data and generating a new collection of variables known as principal component ([25], 2019; [36], 2014). Every re produced component is proportionally related with original variables. The fundamental benefit of PCA is that the principal components of every dataset are orthogonal to each other, so there is no redundant data after pre-processing

Algorithm of PCA:

Input: Data Matrix

Output: Reduced set of arrangements

Step 1: Create N x d information framework (X) with one row has a data point x_n

Step 2: Subtract mean x from each line vector x_n*.*

Step 3: $\boldsymbol{\Sigma}$ *of the yield in step 2 is the Covariance matrix of X.*

Step-4: Find eigenvectors and Eigen values of Σ*.*

Step 5: Identify the largest value of Eigenvector in Principle Component

Step-6: Output PCs

Machine learning algorithms

Decision Tree

To construct the Decision tree model ([37], 2015) we have to follow the following steps:

1. Sorting out the best component in the given dataset that can be designated as the root hub.
2. Subsets are made by parting the dataset accessible for preparation.
3. Singular subset ought to have comparative qualities for a component.
4. Apply for the above advances over and again until you track down the terminal hub for every one of the parts of the tree. The terminal hubs will contain the anticipated qualities.

Random Forest:

The demonstration of Random forest ([29], 2005) are as follows:

1. Select the preparation dataset for directed learning.
2. Pick a specific arrangement of highlights and information tests from the preparation set on an irregular premise.

3. Make a choice tree utilizing the randomized inspected information by choosing the element with the best split as the root hub.
4. Rehash stages 2 and 3 to make various choice trees.
5. The total of the multitude of trees gives the consequence of the random forest.

AdaBoost:

To construct the Decision tree model ([37], 2013) we have to follow the following steps:

1. Initialize the sample weight
2. With the help of each feature construct a decision tree & classify the model
3. Calculate the significance factor from each tree
4. Form a new datasets
5. Repeat step 2 to step 5 until the number of iterations is equal to the number of estimators.
6. Now use the model to predict the output for test datasets.

Table 2. Parameters settings of the applied Algorithm

Algorithm	
KNN	(n_neighbors=5, *, weights='uniform', algorithm='auto', leaf_size=30, p=2, metric='minkowski', metric_params=None, n_jobs=None,
DT	ccp_alpha=0.0,criterion='mse', max_depth=None, max_features=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, presort = 'depreciated', random_state=None, splitter='best',
Random Forest	bootstrap=True, ccp_alpha=0.0, criterion='mse', max_depth=None, max_features='auto', max_leaf_nodes=None, max_samples=None, min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1, oob_score=False, random_state=None, verbose=0, warm_start=False
SVM	C=8, break_ties=False, cache_size=200, class_weight=None, coefo=0.0, degree=3, gamma=0.125, kernel='rbf', max_iter=1, tol=0.001, verbose= False.
AdaBoost	base_estimator=None, n_estimators=50, learning_rate=1.0, algorithm='SAMME.R', random_state=None

RESULT ANALYSIS

In this section, a thorough investigation of the proposed ML techniques is applied on train & test datasets.

Performance Measure:

In any predictive model there are a number of performance metrics are used for testing the model ([6], 2021; [7], 2018a, 2018b, [8] 2020; [11], 2021; [9], 2017a, 2017b, [12]2018a, 2018b, [10] 2020a, 2020b; [15], 2021; Mandal et al., 2019). Mean absolute error (MAE), Mean square error (MSE), Root mean square error (RMSE), and Regression were utilised in this study to evaluate the wind forecast using five machine learning regression models (R2). All these performance metrics are described in Equation (2)-(5). Let n is the number of observations in the test dataset, x_t & y_t are estimated & predicted values of wind speed and E_t is the residual represented in Equation (1) given by

$$E_t = x_t - y_t \quad (1)$$

$$\text{MAE} = \frac{1}{n}\sum_1^n |E_t^2| \quad (2)$$

$$\text{MSE} = \frac{1}{n}\sum_1^n |E_t^2| \quad (3)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_1^n |E_t^2|} \quad (4)$$

$$R^2 = 1 - \frac{\sum_1^n |E_t^2|}{\sum_1^n (x_t - \bar{x})^2} \quad (5)$$

Where, $\bar{x}$ = mean value of the actual wind speed

The tested environment has following features processor and platform: Intel i3, sixth era processor, OS: Ubuntu 20.04 and RAM 8 GB, python 3.7.6, and Jupyter journal 6.03.

Table 3. Description of name of the Model, description & purpose

Name of the Model	**Description**	**Purpose**
DT, RF, AdaBoost , SVM & KNN	Machine learning algorithms with Deterministic Approach	Forecasting
MAE, RMSE, Regression & MSE	Mathematical formulation	Forecasting performance indicator

Five applied machine learning models, their description & the purpose in this research described in Table 3. In this work we applied five ML model: DT, RF, AdaBoost, and SVM & KNN for the forecasting of the wind speed for coming five days where data predicts for 1 hour span. For verifying the best ML model four statistical features: MAE, MSE, RMSE & regression model as a wind forecasting performance indicator.

Benchmark of the Comparison:

In this section we analysis the benchmark of the entire mentioned algorithm with the help of previous section performance indicator. A model is said to be better predictor when it has lower value of error. Coefficient of Regression, R^2, is a positive statistical indicator which indicates higher R2 signify smaller differences experimental & predicted output data. MAE, MSE, & RMSE are the negative statistical error indicator which assessing lower value of this error indicates better prediction accuracy. The entire positive & negative statistical indicator for a model varied due to data size & format. Tables 4 describe the performance indicator for the proposed five machine learning algorithm.

Figure 4 to Figure 8 are representing the comparative study of different algorithm on the basis of MSE, RMSE, MAE, regression & Training Time. Figure 9 represent scatter plot between wind speed v/s wind energy generations for the train datasets.

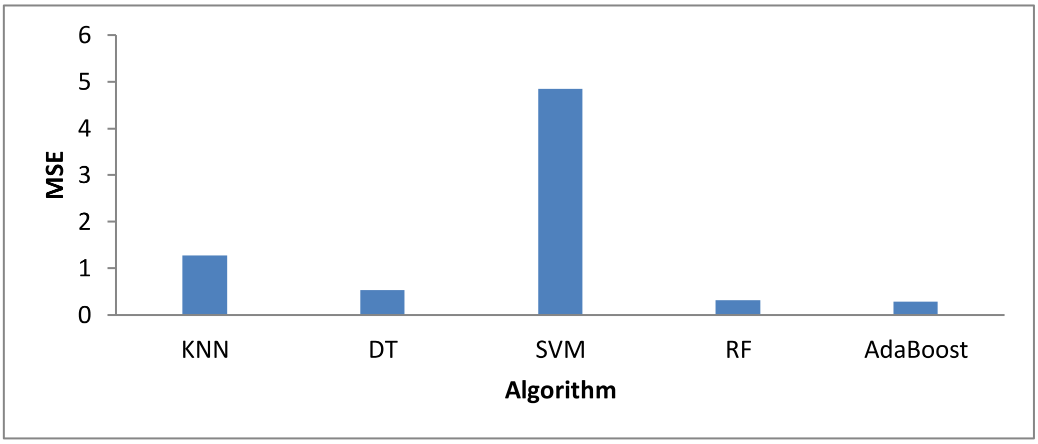

Figure 7. Comparative study based on MSE

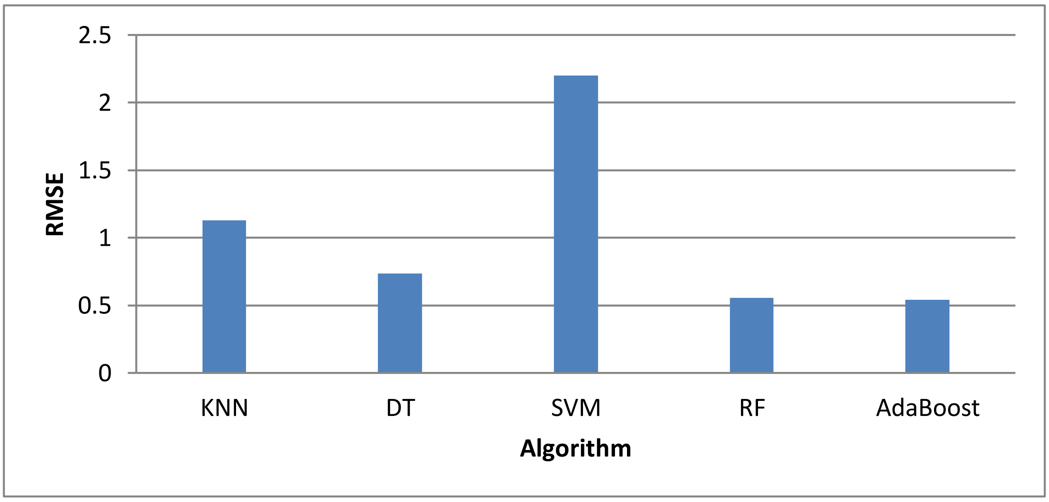

Figure 8. Comparative study based on RMSE

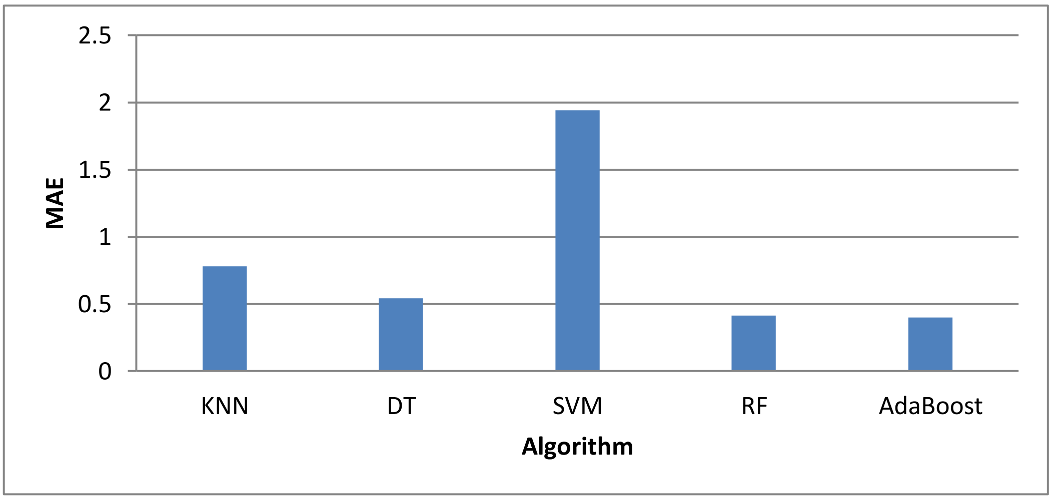

Figure 9. Comparative study based on MAE

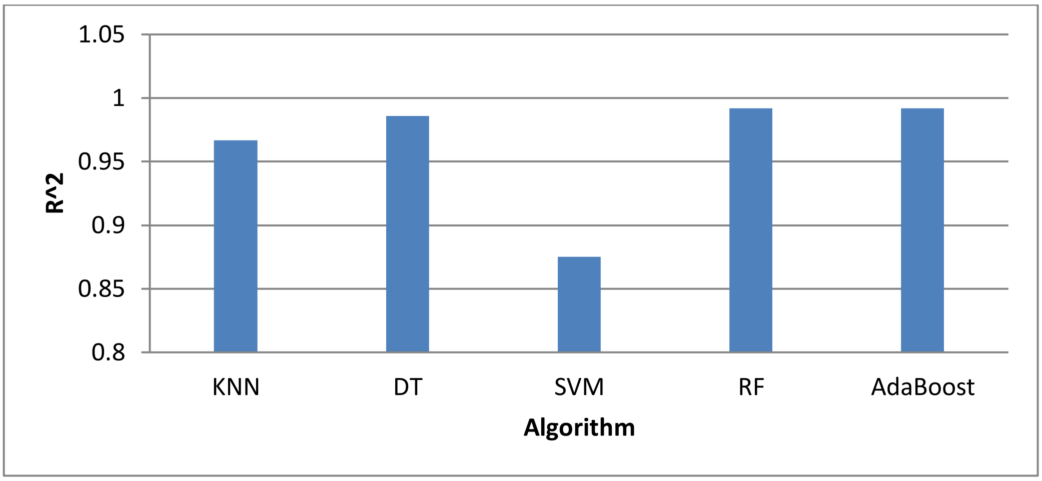

Figure 10. Comparative study based on R^2

Table 4. Performance indicator of the Algorithms

Name of the algorithm	MSE	RMSE	MAE	R^2	Training Time(Sec)
KNN	1.272	1.128	0.780	0.967	62
DT	0.539	0.734	0.539	0.986	32
SVM	4.841	2.200	1.940	0.875	43
RF	0.309	0.556	0.412	0.992	37
AdaBoost	0.209	0.539	0.398	0.992	55

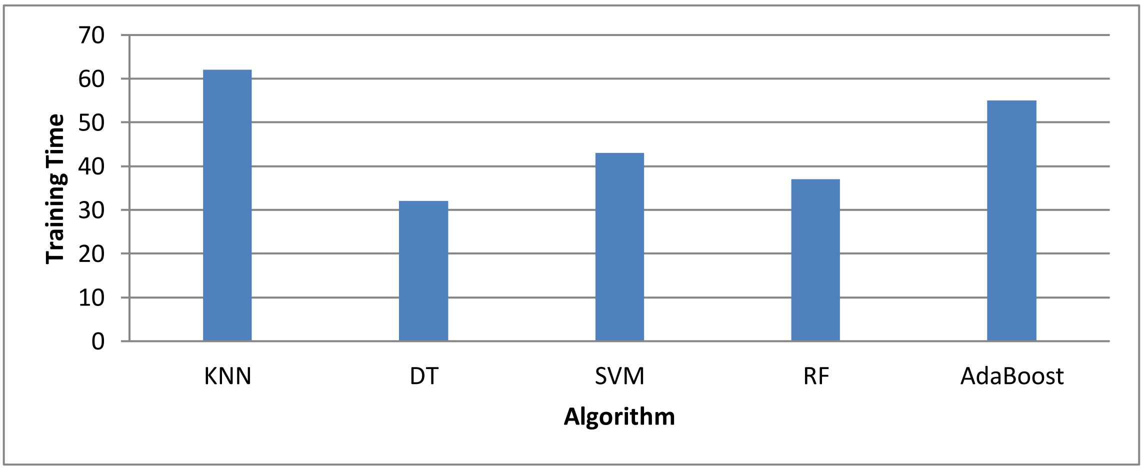

Figure 11. Comparative study based on Training Time

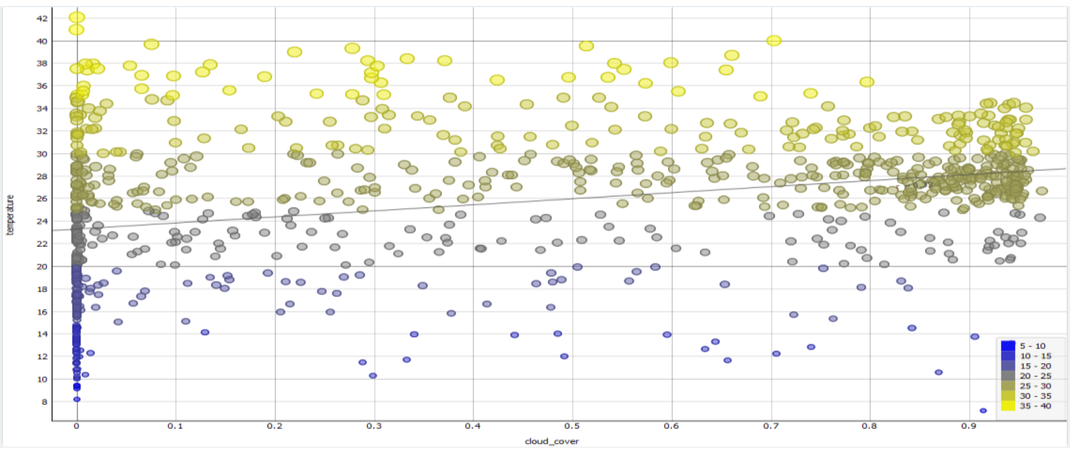

Figure 12. Scatter plot for Temperature v/s cloud cover

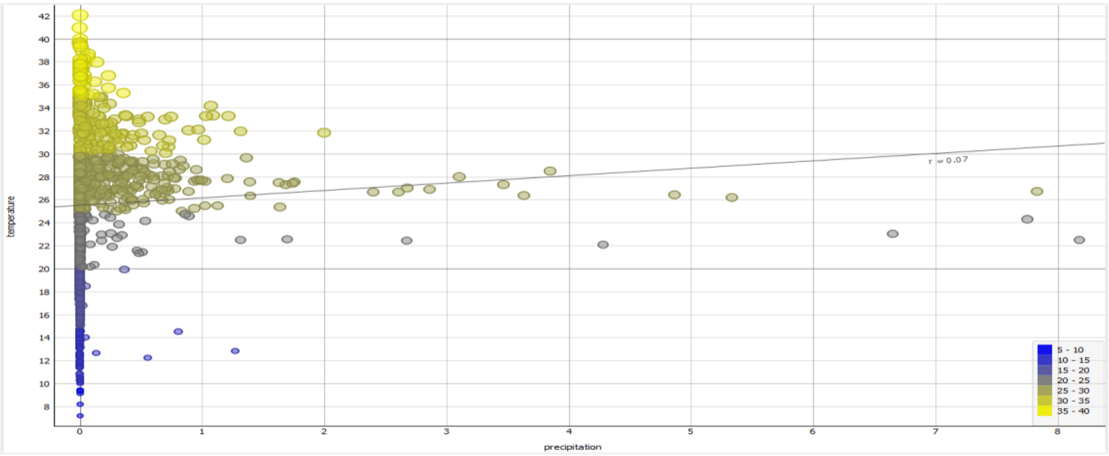

Figure 13. Scatter plot for Temperature versus precipitation

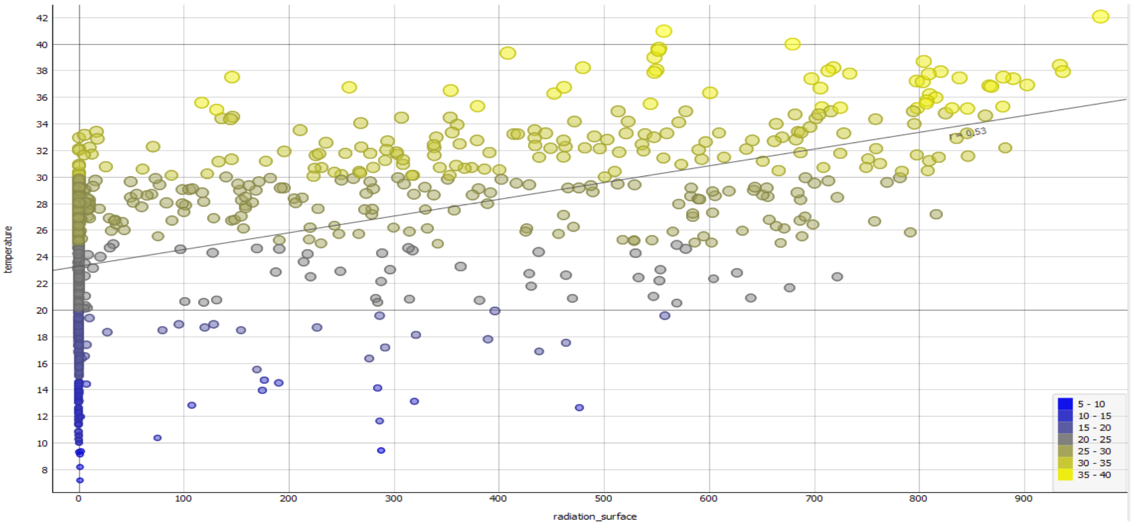

Figure 14. Scatter plot for Temperature versus surface radiation

How the target attributes are correlated with the input attributes by means of numerical value, in present research we used scatter plot. Figure 12 to Figure 14 representing scatter plot between surface cover, precipitation & surface radiation corresponding to temperature.

Comparison with state of art methods:

In this section a comparative study has been performed between a number of mid span time weather forecasting state of art techniques with the present model shown in Table 5. In context different ML techniques was applied to forecasting the weather & RMSE, MAE, & MSE was considered as a performance indicator.

Table 5. State of art for daily temperature prediction

Reference	Attributes	Place	Algorithm	Performance criteria
(N. R. Pal et al., 2003)	Sea level, vapour pressure, humidity , daily temperature & rainfall	Kolkata	MLP-NN & RBF-NN	Min RMSE = 11.4 % for activation function sigmoid & hidden layer and hidden nodes are 1 & 10 respectively.
(Maqsood & Abraham, 2007)	Average daily Temperature, humidity & wind speed	Canada	MLP-NN, RBF-NN & Ensemble	Minimum RMSE & MAE achieved by Ensemble method about 0.2416 & 0.197 respectively
(Ustaoglu et al., 2008)	Daily mean , maximum & minimum temperature	Turkey	MLP-NN, RBF-NN & GRNN	Minimum RMSE achieved by MLP-NN with 2.21 for Levenberg–Marquardt Algorithm
(Mori & Kanaoka, 2007)	Temperature, wind Speed , wind Direction, day light	Tokyo	MLP-NN, SVM & RBFNN	Least MAPE achieved by SVM about to 2.6%

Present model	Temperature, precipitation, snowfall, Snow mass, air density, Cloud cover & radiation surface	Kolkata	KNN,DT, RF, AdaBoost & SVM	Minimum RMSE & MAE achieved by AdaBoost about 0.539 & 0.398 respectively.

CONCLUSION

Weather forecasting is a one kind of complex model of physics where each ingredient of the weather parameters varied around the years. In appropriate states of the weather parameters can cause a huge change in temperature. There is several industries as well as cultivation hugely depends on the temperature forecasting. As the whole world is experiencing ceaseless environmental change and its incidental effects, anticipate the climate with no mistake to guarantee simple and consistent portability, just as protected everyday activities. Among all these three type weather forecasting midterm weather forecasting is very helpful for the cultivation sector. Hence there are several AI models are proposed to improvements in forecasting of weather as well as temperature of any region.

In this paper, an efficient temperature forecasting model is proposed based on hybrid Principal Component Analysis (PCA) empowered machine learning techniques. Datasets comprises 8760 datasets with 7 attributes, for testing purpose we used 876 numbers of datasets. Overall operation has been performed into three phases. In first phase, PCA is applied to eliminate the irrelevant attributes from the datasets to improve the model accuracy. In second phase five machine learning algorithms: KNN, DT, RF, SVM & AdaBoost are used to predict the test datasets. On the last stage four statistical performance indicators: MAE, MSE, RMSE & Regression and training time used to identify the best fitted model. From the result analysis it has been seen that PCA based AdaBoost model outperformed than the other machine learning algorithm except computational time. Hence it has been anticipated the PCA-AdaBoost based model can also be taken as an effective weather forecasting model.

However forecasting of temperature & weather forecasting stills an open challenge for the future research into multi sections. Forecasting of temperature by taking other input attributes like rainfall and dew point, accessibility of real-time weather datasets for achieved better accuracy & designing of multivariable model like forecasting of temperature & wind speed incorporating with input attributes are future scope of this research.

Data Availability

Wind speed data which is used in this study have been taken from the Kolkata, India (https://www.renewables.ninja/).

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