

Weather Forecasting using Artificial Intelligence

Alka Soun, Udhav Mittal , Khushi Kashyap, G. Bhavaaditya Goud, Veerakoti. Mohana Krishna Chaitanya,
Sankaramaddi Hemanth Reddy, Vadla Harshavardhan Chary, Gogula Navateja

Abstract

Traditionally, climate estimation has dependably been performed by considering the environment as a liquid. The current condition of the air is inspected. The future condition of the environment is registered by comprehending numerical conditions of thermodynamics and liquid elements. Yet, this conventional arrangement of differential conditions that oversee the physical model is some of the time shaky under unsettling influences and uncertainties while estimating the underlying states of the air. This prompts an inadequate comprehension of the environmental forms, so it limits climate forecast up to 10 day period, on the grounds that past that climate estimates are essentially unreliable. But Machine learning is moderately hearty to most barometric unsettling influences when contrasted with customary techniques. Another favorable position of machine learning is that it isn't reliant on the physical laws of environmental procedures.

In this report, a reenacted framework is created to foresee different climate conditions utilizing Data Analysis and Machine learning procedures, for example, straight relapse and strategic relapse. The primary wellspring of information to be utilized for directed taking in is to be gathered. The current climate condition parameters ex. temperature and so on are utilized to fit a model and further utilizing machine learning methods and extrapolating the data, the future varieties in the parameters are broke down.

CHAPTER 1 INTRODUCTION

1.1 Introduction

Weather prediction is the task of prediction of the atmosphere at a future time and a given area. In early days, this has been done through physical equations in which the atmosphere is considered as fluid. The current state of the environment is inspected, and the future state is predicted by solving those equations numerically, but we can not determine a very accurate weather for more than 10 days and this can be improved with the help of science and technology.

There are numerous kinds of machine learning calculations, which are Linear Regression, Polynomial Regression, Random Forest Regression, Artificial Neural Network and Recurrent Neural Network. These models are prepared dependent on the authentic information given of any area. Contribution to these models are given, for example, in the event that anticipating temperature, least temperature, mean air weight, greatest temperature, mean dampness, and order for 2 days. In light of this Minimum Temperature and Maximum Temperature of 7 days will be accomplished.

Machine Learning

Machine learning, is relatively robust to perturbations and doesn't need any other physical variables for prediction. Therefore, machine learning is much better opportunity in evolution of weather forecasting. Before the advancement of Technology, weather forecasting was a hard nut to crack. Weather forecasters relied upon satellites, data model's atmospheric conditions with less accuracy. Weather prediction and analysis has vastly increased in terms of accuracy and predictability with the use of Internet of Things, since last 40 years. With the advancement of Data Science, Artificial Intelligence, Scientists now do weather forecasting with high accuracy and predictability.

USE OF ALGORITHMS:

There are different methods of foreseeing climate utilizing Regression and variety of Functional Regression, in which datasets are utilized to play out the counts and investigation. To Train the calculations $\frac{3}{4}$ size of information is utilized and $\frac{1}{4}$ size of information is named as Test set. For Example, in the event that we need to anticipate climate of Austin Texas utilizing these Machine Learning calculations, we will utilize 6 Years of information to prepare the calculations and 2 years of information as a Test dataset.

On the as opposed to Weather Forecasting utilizing Machine Learning Algorithms which depends essentially

on reenactment dependent on Physics and Differential Equations, Artificial Intelligence is additionally utilized for foreseeing climate: which incorporates models, for example, Neural Networks and Probabilistic model Bayesian Network, Vector Machines. Among these models Neural Network is widely utilized as it is efficient to catch more conditions of past weather report and future weather conditions.

In any case, certain machine learning calculations and Artificial Intelligence Models are computationally costly, for example, utilizing Bayesian Network and machine learning calculation in parallel.

To finish up, Machine Learning and Artificial Intelligence has enormously change the worldview of Weather estimating with high precision and predictivity. What's more, inside the following couple of years greater progression will be made utilizing these advances to precisely foresee the climate to avoid catastrophes like typhoon, Tornados, and Thunderstorms.

Machine learning has the following main algorithms:

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

Supervised learning: This is a set of predictors. These predictors are independent variables. The objective of this learning algorithm is to predict from this set of independent variables. The prediction is for the outcome variable. This is a dependent variable. With the set of independent variables, a function is generated that facilitates the allocation of our inputs to the desired outputs. To achieve a certain precision in our training data, the machine is continuously trained. Examples of supervised learning are linear regression, logistic regression, KNN decision tree, random forest, etc.

Uncontrolled learning: in this algorithm, there is no particular goal or result that can be estimated or predicted. It is used to group into different groups, which is used for segmentation into different groups for specific interventions. Some examples of unsupervised learning are K-Means, Apriori's algorithm.

Reinforcement learning: certain decisions have been made when training the machine with this algorithm. It works so that the machine is exposed to conditions in any environment. The machine is continuously trained with the trial and error method. To make accurate business decisions, the machine learns from past experience by capturing the best possible knowledge. Some examples of learning by reinforcement are the Markov decision process.

1.2 Problem Statement

Heavy rainfall can lead to numerous hazards, for instance:

flooding, including danger to human life, harm to structures and framework, and loss of products and domesticated animals. avalanches, which can compromise human life, upset transport and interchanges, and cause harm to structures and foundation. Where overwhelming precipitation happens with high breezes, hazard to ranger service crops is high..

In the case of initial treatment of patients, the probability of survival has increased significantly with early diagnosis of breast cancer. With proper tumor classification, unnecessary treatment can be avoided. Each volume should be treated differently. Therefore, if there is no proper diagnosis then there is a high risk of death for the patient. Correct diagnosis of breast cancer and classification of tumors in benign and malignant tumors is an area of investigation.

For example if we consider an area affected by tropical cyclone the fundamental impacts of tropical cyclone incorporate heavy rain, strong wind, huge tempest floods close landfall, and tornadoes. The devastation from a tropical cyclone, for example, a sea tempest or hurricane, depends for the most part on its power, its size, and its area. Tropical tornados act to evacuate woods shade and additionally change the scene close beach front zones, by moving and reshaping sand ridges and causing broad disintegration along the drift. Indeed, even well inland, overwhelming precipitation can prompt mudslides and avalanches in rugged regions. Their belongings can be detected after some time by concentrate the convergence of the Oxygen-18 isotope inside caverns inside the region of typhoons' ways. So we are providing a better way to get accurate predictions.

As mentioned above, the benefits of identifying important features of mechanical learning, complex data sets, play an important role in forecasting of weather. Since the best results can be achieved with engineering learning algorithms, we should use these techniques to aware people from natural disasters. This is because learning engineering algorithms can provide more accurate results. Apart from this, the results are achieved at a short time and people get enough time to do preparations or to escape from that place .

1.3 Objectives

Our project aims to predict the Weather and Atmosphere conditions using the previous dataset of the weather forecasting with a focus on improving the accuracy of prediction. This will increase the accuracy of the weather prediction and we will get accurate results than the traditional methods. Our dataset consists of max and min. temperature of everyday from the specific location.

Classifications:

When gathering datasets to give to the models there are sure parameters which are called as ordered information which incorporates: snow, rainstorm, rain, mist, cloudy, for the most part overcast, halfway shady, scattered mists, and clear. These can be additionally ordered into four classes.

1. Rain, tempest, and snow into precipitation
2. For the most part shady, foggy, and cloudy into exceptionally shady
3. Scattered mists and somewhat shady into modestly shady
4. Clear as clear

Thus our aim is to provide accurate result in order to provide correct prediction of weather for future so in critical conditions people can be aware of upcoming natural calamities.

1.4 Methodology

The dataset utilized in this arrangement will be gathered from Weather Underground's complementary plan API web benefit. I will utilize the solicitations library to collaborate with the API to pull in climate information since 2015 for the city of Lincoln, Nebraska. When gathered, the information should be process and collected into an organization that is appropriate for information examination, and afterward cleaned.

Then we will concentrate on examining the patterns in the information with the objective of choosing fitting highlights for building a Linear Regression, Polynomial Regression. We will examine the significance of understanding the suppositions vital for utilizing a Linear and Polynomial Regression show and exhibit how to assess the highlights to fabricate a hearty model. This will finish up with a discourse of Linear and Polynomial Regression show testing and approval.

Atlast we will concentrate on utilizing Neural Networks. I will look at the way toward building a Neural Network show, deciphering the outcomes and, by and large precision between the Linear and Polynomial Regression demonstrate worked earlier and the Neural Network display.

We have a problem statement which comes under the category of Classification. It is a multiclass classification in which the classes given to us are

1. Rain, tempest, and snow into precipitation
2. For the most part shady, foggy, and cloudy into exceptionally shady
3. Scattered mists and somewhat shady into modestly shady

4. Clear as clear

Our aim is to classify the given data into the above given classes. In order to do so, we have to first analyze the data given to us. For analyzing the features, we are using different techniques.

The training of model can be done in many ways. It depends on how the data is prepared for further processing. The data can be used directly depending on the situation or the data can be used to form a histogram. After these modifications, we choose a particular model on which we will train our data. This model can be: Linear regression, Logistic Regression, SVM, Neural Networks, Decision Tress, K-Nearest Neighbors etc. Parameter tuning can also be done in order to increase our accuracy.

3.1 Analysis

CHAPTER 3 SYSTEM DEVELOPMENT

The learning procedure starts with the perception of information, so examples can be discovered in information and prevalent choices can be taken later on which depend on the precedents gave. The principle point is to enable PCs to learn without human help or collaboration and modify their activities as needs be.

The amount and size of malignant growth databases are expanding quickly, yet most are not dissected to discover covered up and profitable learning. Machine learning procedures can be utilized to find shrouded connections and examples. Models created utilizing machine learning systems enable specialists to settle on exact choices.

Accordingly, we utilize programmed learning strategies, for example, random forests, linear regression, polynomial regression, and so on to prepare our machine. The gadget adjusts to the predefined information record and gains from the predetermined parameters. From that point forward, machine learning strategies have turned out to be precise in a few fields before. Along these lines, the utilization of machine learning is helpful for the conclusion of malignant growth. Collapsing neural systems work surprisingly better than linear regression, polynomial regression and Random Forests. This is on the grounds that, at every one of the dimensions, the weights proceed to return and attempt to diminish the mistake.

The most critical piece of our task is the examination of data when programmed learning methods are utilized.

To dissect the pictures, we utilize a few descriptors, for example, nearby double examples, ORB, edge nearness measurements without parameters (PFTAS), GLCM. These element extractors help remove the usefulness of each picture. Subsequent to seeing these element vectors, we can at long last train our machine in like manner. At last, this will enable us to get an exact determination of the forecast.

The most extreme exactness was accomplished when Parameter Free Threshold Adjacency Statistics was utilized as the component extractor and SVM was utilized as the Machine Learning Algorithm. The best outcome was accomplished when parameters were tuned in like manner. With the end goal to tune parameters and gets quick outcomes, Grid Search technique was utilized. In network seek strategy, a scope of parameters is given to the classifier and the calculation at long last takes up the best blend of all the given parameters. The best arrangement of parameters is taken with the end goal that it gives the most extreme exactness.

3.2 System Design

The record has just been separated into train set and test set. Each information has just been labeled. First we take the trainset organizer.

We will train our model with the help of histograms. The feature so extracted is stored in a histogram. This process is done for every data in the train set. Now we will build the model of our classifiers. The classifiers which we will take into account are Linear Regression, Polynomial Regression, Random Forest and Neural Networks. With the help of our histogram, we will train our model. The most important thing to in this process is to tune the parameters accordingly, such that we get the most accurate results.

Once the training is complete, we will take the test set. Now for each data variable of test set, we will extract the features using feature extraction techniques and then compare its values with the values present in the histogram formed by train set. The output is then predicted for each test day. Now in order to calculate accuracy, we will compare the predicted value with the labeled value. The different metrics that we will use are confusion matrix, accuracy score, f1 score etc.

3.3 Model Development

Our strategy for model improvement is exploratory. The objective of our undertaking is to ensure the conclusion of malignancy with greatest accuracy. This must be accomplished by exploring different avenues regarding distinctive systems from a specific field. We have considered the programmed learning descriptors and algorithms.

The Machine Learning Algorithms that we are using are:

- Linear Regression
- Polynomial Regression
- Random Forest
- Neural Networks

Subsequently our point is to locate the best mix which will furnish us with greatest precision. Along these lines this task is absolutely test based. In addition parameter tuning is a noteworthy piece of any Machine Learning Algorithm. Regardless of whether the calculation works exceptionally solid in specific conditions, at that point too because of terrible determination of parameters, the precision could be low. In this manner we likewise need to center around the right arrangement of parameters. Hence parameter tuning must be done in whichever show we pick.

Parameter tuning should either be possible physically or by utilizing the lattice seek technique. Network looking is the procedure in which information is checked with the end goal to discover ideal parameters for some random model. Contingent upon the kind of model that we are utilizing, tuning of specific parameters is vital. Framework seeking applies to a solitary model sort as well as number of models. Network looking can be connected in machine learning with the end goal to ascertain the best parameters for its utilization in some random model. It very well may be computationally greatly costly and may set aside a long opportunity to keep running on the machine. Matrix Search constructs a model on every conceivable parameter mix. At that point it repeats through every parameter blend lastly stores a model for each mix.

CHAPTER 4 ALGORITHMS

4.1 Simple Linear Regression

Simple linear regression is a factual strategy that enables us to abridge and consider connections between two ceaseless (quantitative) factors: One variable, signified x , is viewed as the indicator, logical, or free factor. The other variable, indicated y , is viewed as the reaction, result, or ward variable.

Since alternate terms are utilized less much of the time today, we'll use the "predicator" and "reaction" terms to direct to the factors experienced in this course. Alternate terms are referenced just to give you knowledge of them that you should experience them in different fields. Straightforward simple linear regression gets its descriptor "basic," since it concerns the investigation of just a single indicator variable. Conversely, different

straight relapse, which we examine later in this course, gets its descriptor "numerous," on the grounds that it concerns the investigation of at least two predicator factors.

The previous data is given in Table 1 .We can observe a positive relationship between X and Y. There can be a relation observed between X and Y, Higher the estimation of X more accurate will be the prediction of Y.

Table 1. Example data.

X	Y
5.00	2.25
4.00	3.75
3.00	1.30
2.00	2.00
1.00	1.00

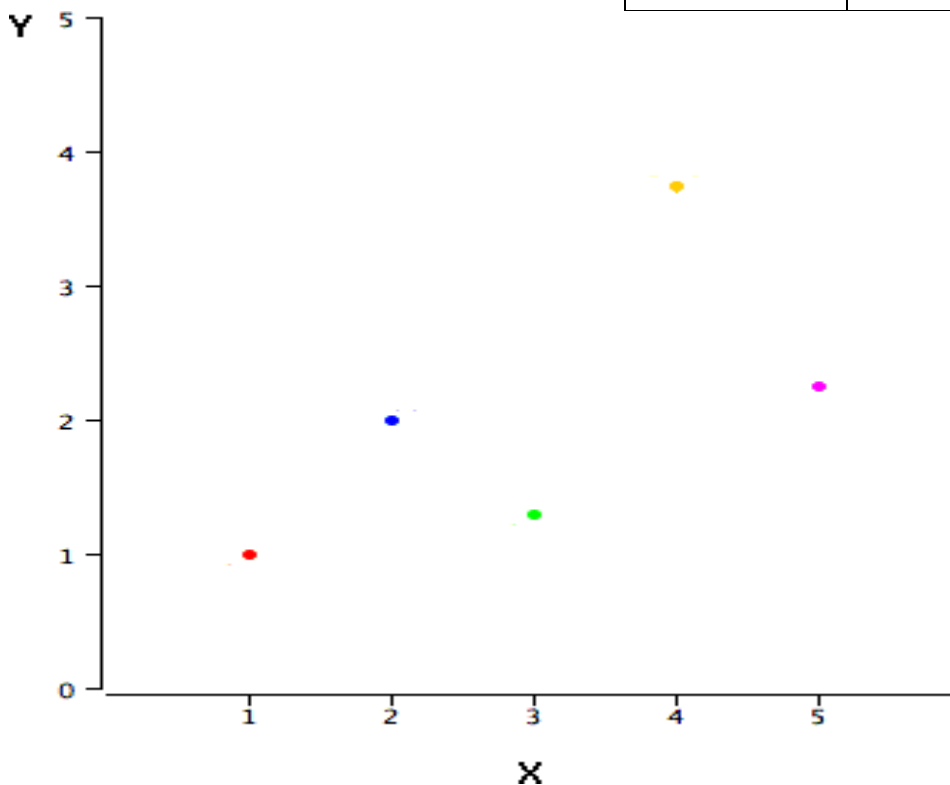


Figure 1.Scatter Graph of information.

Linear regression consist of exploring the best straight line through the points also known as regression line . The dark line in Figure 2 is the regression line and consists of the expected score on Y for every estimation of X. The vertical lines from the focuses to the regression line speak to the blunders of expectation. As we can see in the graph, the red point is very very close to the regression line, its acuuracy is better. Conversely, the yellow point is very far from the line.than the regression line and subsequently its mistake of forecast is vast.

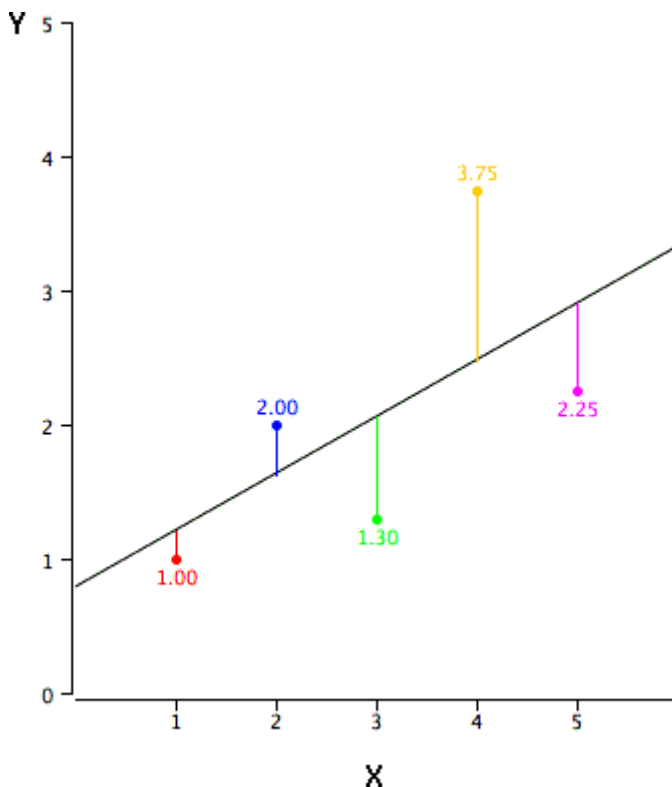


Figure 2. A scatter graph of the data with regression line.

The regression line is used for predictions and the values that has been given in graph are the actual data set given to the model. We use colored vertical lines and regression line for the comparison of error.

The prediction error for a point is the subtraction of the value of the point from the predicted value (the value on the line). Table 2 shows the predicted values (Y') and the prediction errors ($Y - Y'$). For example, the second point has a Y of 2.00 and a predicted Y (called Y') of 1.635. Therefore, its prediction error is 0.365.

Table 2. Example data.

X	Y	Y'	Y-Y'	(Y-Y') ²
5.00	2.25	2.910	-0.660	0.436
4.00	3.75	2.485	1.265	1.600
3.00	1.30	2.060	-0.760	0.578
2.00	2.00	1.635	0.365	0.133
1.00	1.00	1.210	-0.210	0.044

You may have seen that we didn't indicate what is implied by "best-fitting line." By far, the most regularly utilized criterion for the best-fitting line is the line that limits the whole of the squared mistakes of expectation. That is the criterion that was utilized to discover the line in Figure 2. The last column in Table 2 depicts the squared prediction errors. The sum of the squared prediction errors shown in Table 2 is lesser than it would be for any other regression line.

The formula for a regression line is $Y' = bX + A$

where Y' is the score prediction, the slope of line is b while A is the Y intercept. The equation is

$$Y' = 0.425X + 0.785 \text{ If } X = 1,$$

$$Y' = 1.21. \text{ If } X = 2, Y' = 1.64.$$

4.2 Polynomial Linear Regression

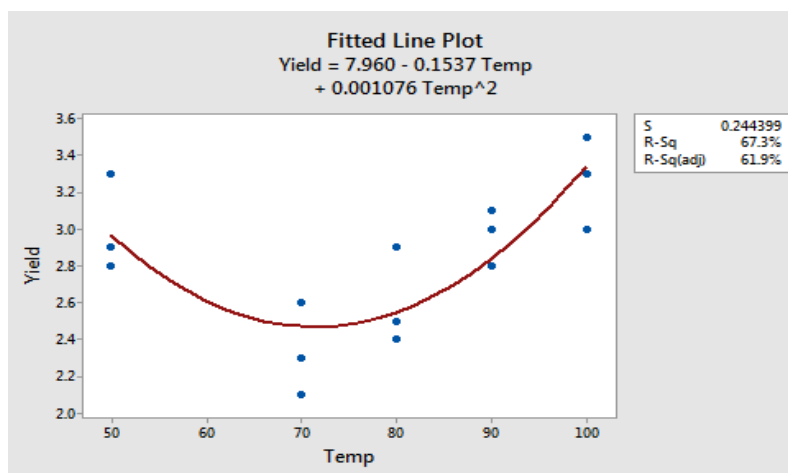
It is a type of linear regression in which the relationship between the input factors x and the yield variable y is displayed as a polynomial. Albeit polynomial regression fits a nonlinear model to the information, as a measurable estimation issue it is linear, in the feeling that the regression work is linear in the obscure

parameters that are evaluated from the information. Thus, polynomial regression is viewed as a unique instance of linear regression. Once in a while, a plot of the residuals versus a predictor may recommend there is a nonlinear relationship. One approach to attempt to represent such a relationship is through a polynomial regression demonstrate. A model for such a single predictor, X , is:

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \dots + \beta_h X^h + \epsilon,$$

h is **degree** of the polynomial. For lower degrees, the relationship has an explicit name (i.e., $h = 2$ is called quadratic, $h = 3$ is called cubic, $h = 4$ is called quartic, etc). In spite of the fact that this model takes into consideration a nonlinear relationship among Y and X , polynomial regression is as yet viewed as linear regression since it is linear in the regression coefficients, $\beta_1, \beta_2, \dots, \beta_h$.

Figure 3. A Sample Polynomial regression plot with best fitted line



With the end goal to evaluate the condition above, we would just need the reaction variable (Y) and the predictor variable (X). In any case, polynomial regression models may have other predictor factors in them too, which could prompt connection terms. So as should be obvious, the essential condition for a polynomial regression display above is a generally simple model, however you can envision how the model can develop contingent upon your circumstance!

Generally, we actualize indistinguishable investigation techniques from done in numerous linear regressions.

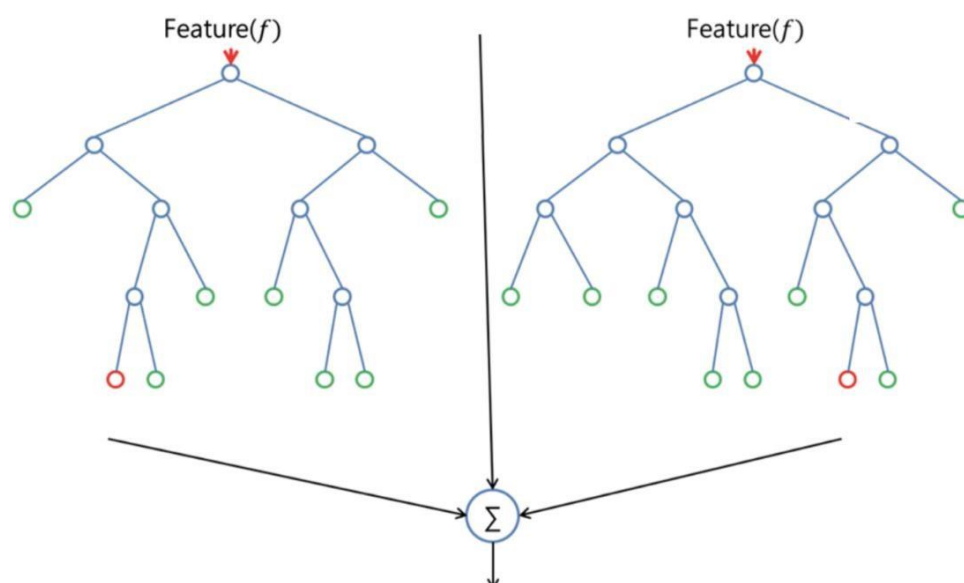
4.3 Random Forest Regression

Random Forest is an adaptable, simple to utilize machine learning algorithm which produces, even without hyper-parameter tuning, a consistent outcome more often than not. It is likewise a standout amongst the most utilized algorithms, as it is straightforward and can very well be utilized for both classification and regression tasks.

Random Forest is a type of supervised learning algorithm. As is evident from its name, it makes a forest and makes it by a random way of selection. The "forest" it assembles, is an outfit of Decision Trees, prepared with the "bagging" strategy more often than not. The general thought of the bagging technique is that a mix of learning models expands the general outcome.

To state it in simple words: It forms various decision trees and clubs them all together to get a more accurate prediction.

Random Forest (RF) is an extremely adaptable and simple to utilize Machine Learning (ML) calculation. It creates exceptionally precise outcomes even without the high degree of hyper-parameter tuning. Irregular Forest (RF) is additionally a standout amongst the most utilized Machine Learning (ML) calculations. This is on the grounds that it is extremely basic and can likewise be utilized for both characterization and relapse tests.



Random Forest as two tree .

Fundamentally there are two phases in Random Forest (RF) calculation. First is irregular timberland creation. Second is to play out an expectation from the recently made irregular woods classifier. The entire procedure can be given as:

:

- i) Select randomly “K” features from the total “m” features. Here $k \ll m$.
- ii) Now Among these “K” features, using the best split point calculate the node “d” .
- iii) Then split the node into its daughter nodes by using the best split.
- iv) Repeat all the steps from a to c until “l” number of nodes has been finally reached.

Now build the forest by repeating steps a to d for “n” number times in order to create “n” number of trees.

4.4 Logistic Regression

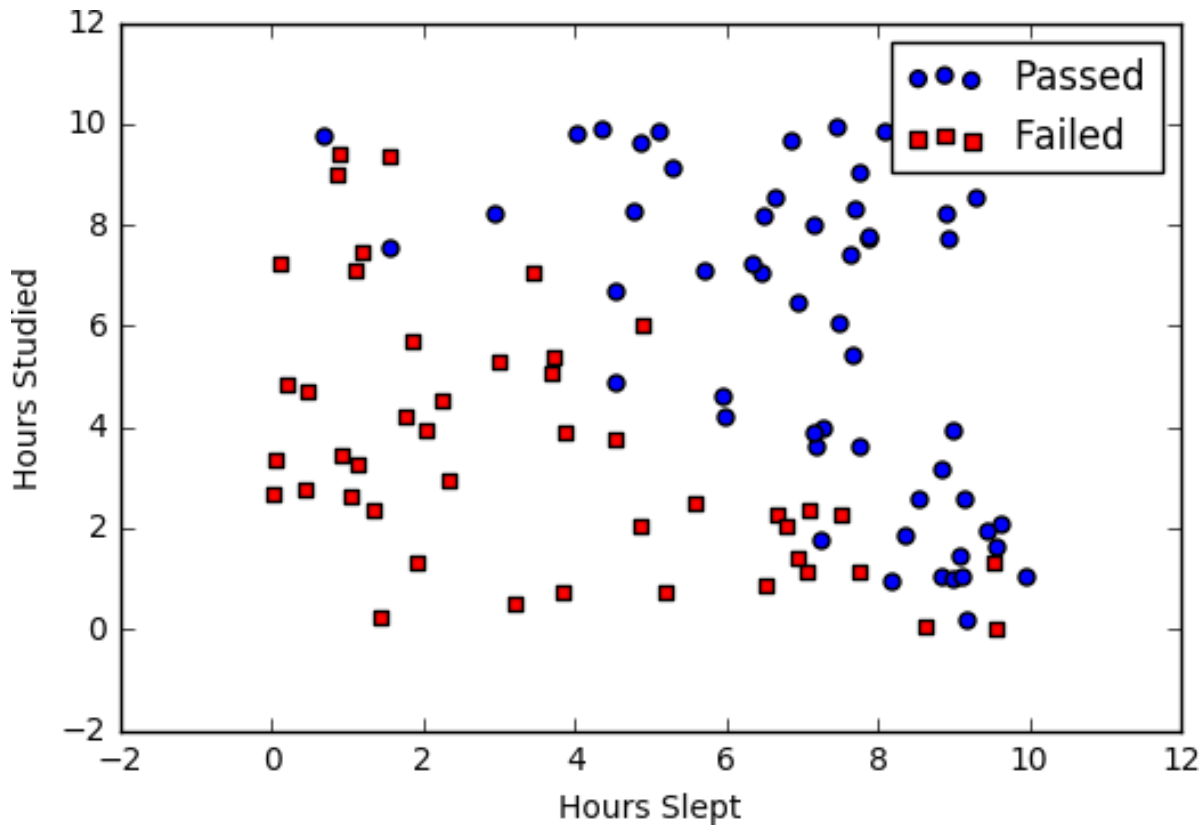
Logistic regression is a classification algorithm used to allocate perceptions to a discrete arrangement of classes. Dissimilar to linear regression which yields persistent number qualities, logistic regression changes its yield utilizing the logistic sigmoid capacity to restore a likelihood esteem which would then be able to be mapped to at least two discrete classes.

Let's assume we're given information on understudy test results and our objective is to foresee whether an understudy will pass or fall flat dependent on number of hours dozed and hours spent considering. We have two highlights (hours rested, hours contemplated) and two classes: passed (1) and fizzled (0).

Studied	Slept	Passed
4.84	9.62	1
8.61	3.22	0
5.42	8.22	1
9.21	6.33	0

Table : Number of ours slept versus number of hours studied.

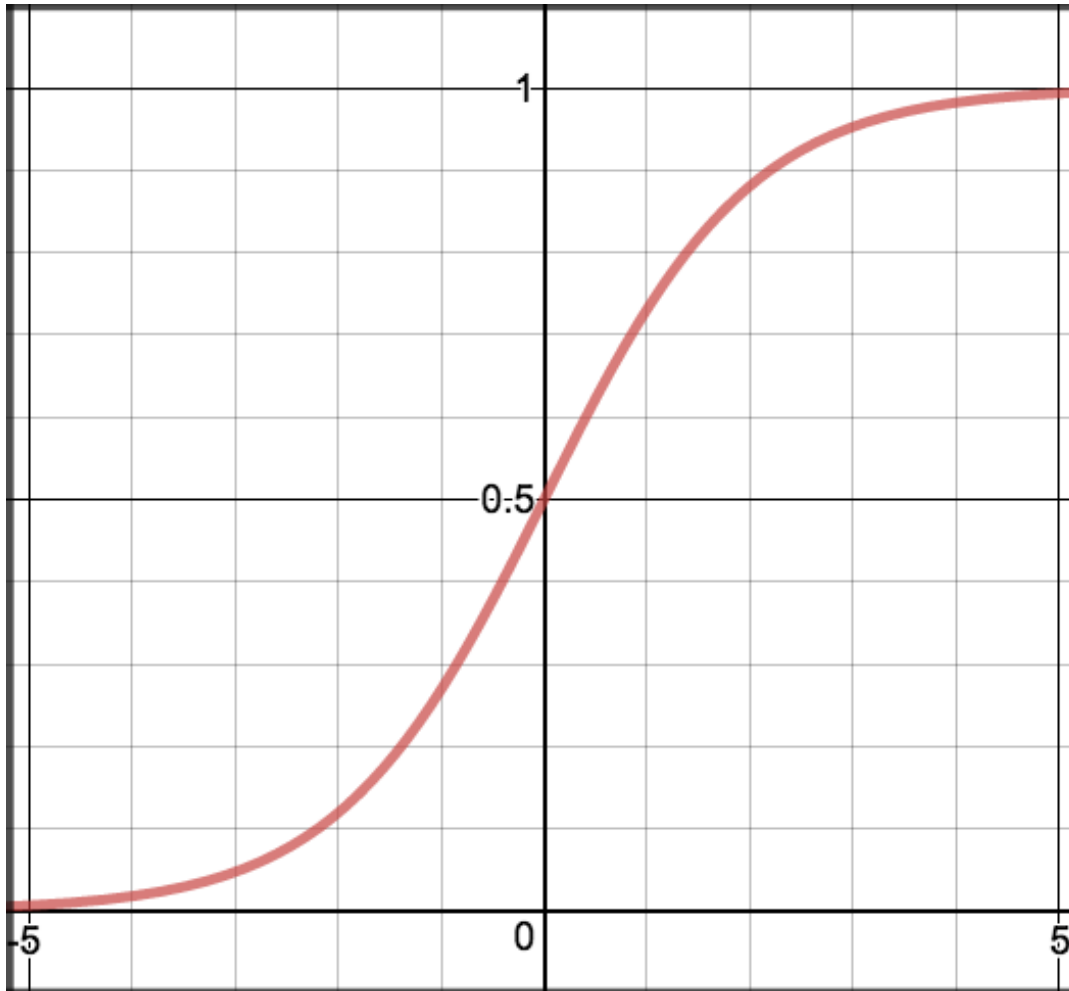
Graphically we could represent our data with a scatter plot.



Sigmoid Function

So as to delineate qualities to probabilities, we utilize the sigmoid function. The capacity maps any genuine incentive into another incentive somewhere in the range of 0 and 1. In machine learning, we utilize sigmoid to outline the probabilities.

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad \dots(1)$$



Graph: Sigmoid Function

4.5 Neural Networks

A neural system (NN) is a worldview of data handling that is roused by the working of organic sensory systems, for example, our cerebrum, which forms data. The primary component of this worldview is the extraordinary novel structure of our data preparing framework. This framework comprises of countless interconnected preparing components (neurons) cooperating. Their fundamental objective is to take care of particular issues. Neural systems (NN) more often than not learn by precedent.

A Neural Networks (NN) is arranged for a specific application. This incorporates information characterization or example acknowledgment through a precise learning process. Learning in the organic frameworks by and large includes acclimations to the principle synaptic associations that typically exist between the neurons. Same is the situation with Neural Networks (NN).

Initiation Functions: Neuron can't learn with just a straight capacity that is appended to it. Any non-straight enactment capacity will dependably give it a chance to pick up as per the distinction as for mistake. Consequently initiation capacities are required.

Different types of activation functions that we will use in this project are:

4.4.1 *Linear:* This function is a line or can also be called linear. Therefore, the output of these functions will not be confined to any range.

Equation can be given as: $f(x) = x$

Range can be given as: (-infinity to infinity)

It never helps with the complexity or various different parameters of the usual data that is generally fed to the neural networks.

4.4.2 *Logistic:* The Sigmoid Function or the Logistic Function curve looks like a solid S-shape.

The reason why we mainly use logistic function is because of its existence between (0 to 1). Hence, it is particularly used for models where the output to be predicted is probability. Since the probability exists only in the range of 0 and 1, logistic is the right choice. The function is also differentiable. Thus we can find the slope of the logistic function curve at any two given points. The logistic function is monotonic but its derivative is not. The softmax function can be said as a more generalized logistic activation function as it is used for multiclass classification.

4.4.3 *tanh:* tanh is also similar to logistic sigmoid but better. The range of this function is from (-1 to 1) and it is also sigmoidal (s - shaped). The advantage in tanh is that the negative inputs will be strongly mapped negative and zero inputs will be mapped close to zero in the tanh graph. This function is also differentiable. The function is also monotonic whereas its derivative is not. tanh is generally used in classification between two classes.

4.4.4 *Rectified Linear Unit (ReLU):* The Regulated Linear Unit (ReLU) is currently the most used activation function in the world. Since then, it has been used in almost all convolutional neuronal networks or deep learning. Its range can be specified as follows: [0 to infinity] The function is

monotonic and also its derivative. However, the problem is that all negative values become zero immediately, which quickly reduces our model's ability to properly adjust or train the given data. This means that as soon as the negative entries that are passed to the ReLU activation function, the value in the graph immediately to zero, the resulting graph is affected because the negative values are not assigned accordingly

CHAPTER 5 PERFORMANCE ANALYSIS

The dataset being used for our prediction models comprises of weather records of the city in focus collected over a period of time using various different parameters like temperature, humidity, atmospheric pressure, and so on. Till date it consists of a record of weather over a period of 20 years (1997-2016).

Characteristics

The data enclosed in our dataset is classified into the following categories:-

- i) Temperature
- ii) Atmospheric pressure
- iii) Humidity
- iv) Fog
- v) Dew point

Temperature is a measure of the degree of hotness or coldness of the surroundings. It, like all weather conditions, varies from instance to instance. Similarly, atmospheric pressure and humidity, that plays a vital role in predicting whether an area will receive precipitation or not, is also included in the dataset. Details about fog and dew point are included in the dataset as well, as they only contribute to improving the accuracy of the predictions made by the prediction models.

All the data gathered in the dataset was collected from Wunderground that has an easy to use API, which makes data collection all the more simpler.

Given below is a tabular representation of the data collected in the dataset:

5.2

Dataset

Date and time	Precipitation	Atmospheric pressure	Humidity	Fog	Temperature
18-11-1996 11:00	0	934	2	0	18
18-11-1996 12:00	0	936	3	0	19
18-11-1996 1:00	0	932	4	0	20
18-11-1996 2:00	0	934	4	0	19
18-11-1996 3:00	0	934	3	0	17
18-11-1996 4:00	0	936	2	0	16

5.3

Result

The results of the implementation of the project are demonstrated below.

Multiple Linear Regression:

This regression model has high variance, hence turned out to be the least accurate model. Given below is a snapshot of the actual result from the project implementation of multiple linear regression.

S.No	Actual Value	Predicted Value
1.	0	0.0459157
2.	0	0.0423579
3.	0	0.0474239
4.	1	0.8654278
5.	0	0.0325468
6.	0	0.0023542
7.	0	0.1236582

Table 5.4.1: Actual vs Predicted Values

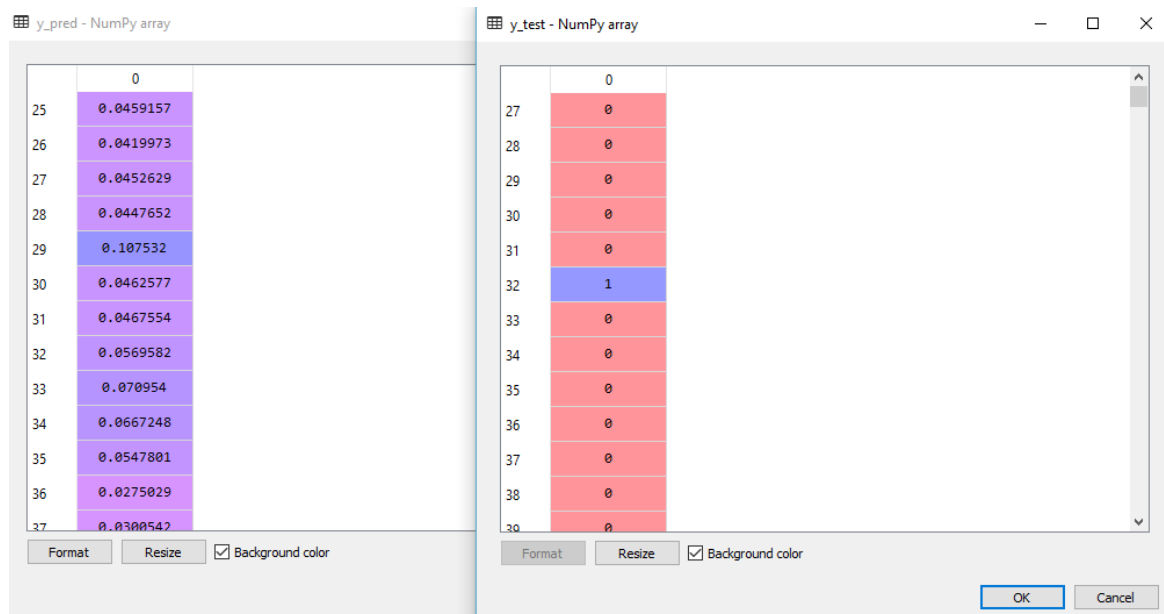


Figure 5.4.1: Predicted and actual values using Multiple linear regression.

Polynomial Linear Regression:

This regression model is much more accurate than the multiple linear regression model, hence it made predictions that were more closer to the actual result than linear regression. Below is a snapshot of its implementation in the code, and the result it displayed.

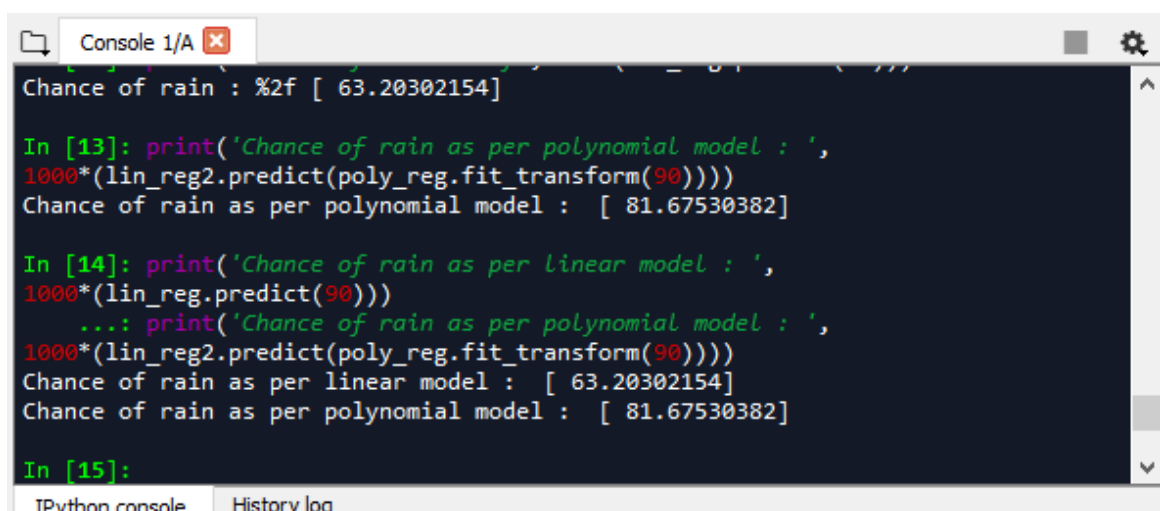


Figure 5.4.2: Comparison of results from linear regression and Polynomial regression

S.no	Actual Value	Predicted Value
1	0	0.0214568
2	0	0.2669756
3	1	0.8165476
4	0	0.0165959
5	1	0.6326548
6	1	0.7656548
7	0	0.0436597

Table 5.4.2 : Actual vs Predicted values from Polynomial regression.

Logistic regression:

This regression technique is used to classify the predictions. Here, I used binary logistic regression. The result of this regression technique was justified using the confusion matrix. The accuracy was 97%, as per the confusion matrix. Below is a snapshot of the same.

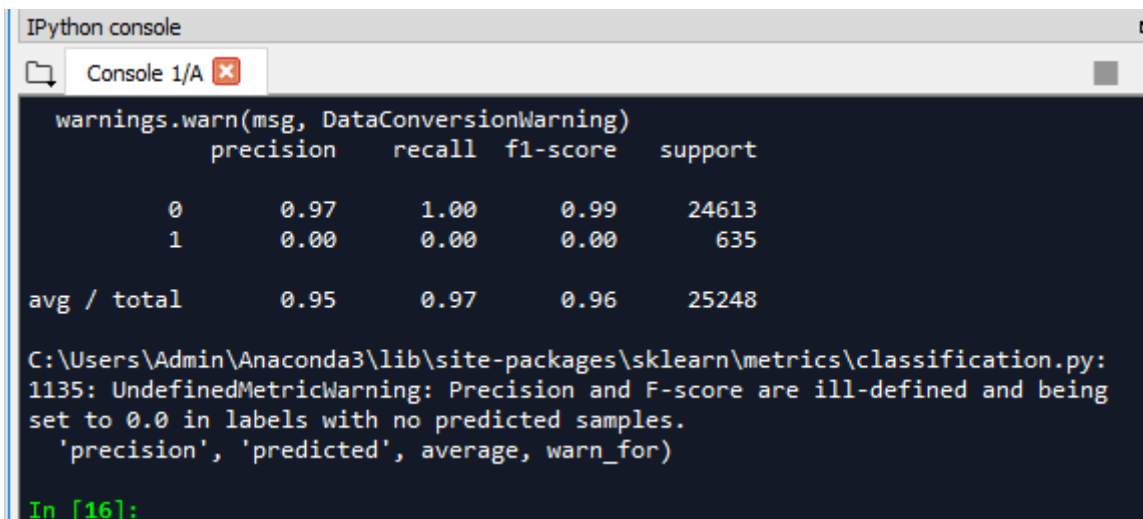


Figure 5.4.3: Confusion matrix for Logistic Regression.

	Precision	Recall	F1-score	Support
0	0.97	1.00	0.99	24613
1	0.00	0.00	0.00	635
Avg/total	0.95	0.97	0.96	25248

Table 5.4.3: Confusion Matrix for Logistic regression.

Random Forest Regression:

Out of all the regression techniques, Random Forest was the one with the maximum accuracy. Random forest is extremely versatile and widely used because of this feature.

Given below is a snapshot of the result generated, compared to the actual data. The random forest was populated with 300 decision trees.

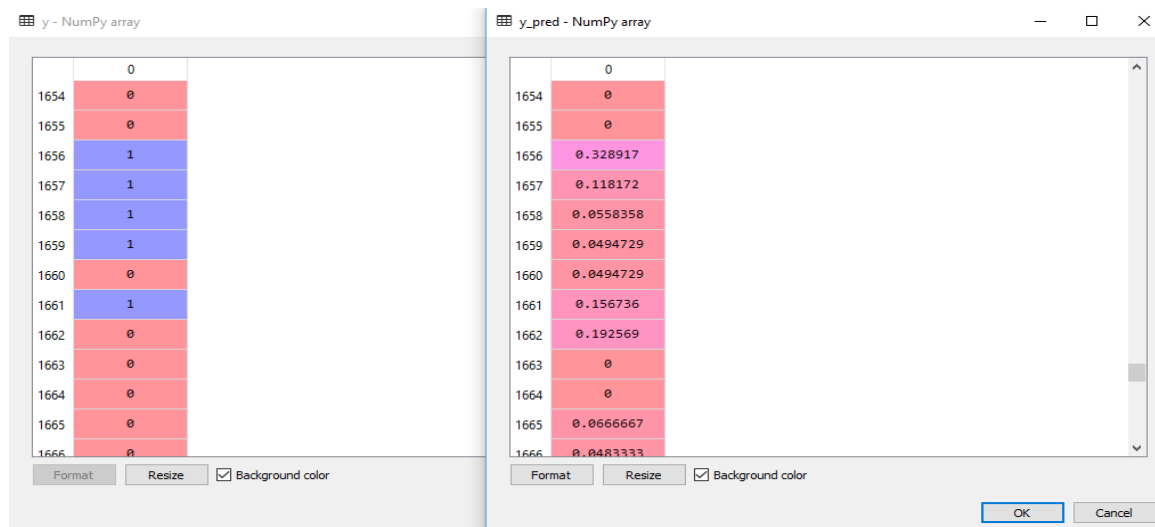


Figure 5.4.4: Actual and predicted values using Random Forest Regression.

S.No	Actual Values	Predicted Values
1	0	0
2	0	0
3	1	0.324546
4	1	0.121647
5	1	0.564642
6	1	0.195487
7	0	0

Table 5.4.4: Actual vs Predicted values from Random Forest Regression.

CHAPTER 6 CONCLUSION

All the machine learning models: linear regression, various linear regression, polynomial linear regression, logistic regression, random forest regression and Artificial neural systems were beaten by expert climate determining apparatuses, in spite of the fact that the error in their execution reduced significantly for later days, demonstrating that over longer timeframes, our models may beat genius professional ones.

Linear regression demonstrated to be a low predisposition, high fluctuation model though polynomial regression demonstrated to be a high predisposition, low difference model.

Linear regression is naturally a high difference model as it is unsteady to outliers, so one approach to improve the linear regression model is by gathering of more information.

Practical regression, however, was high predisposition, demonstrating that the decision of model was poor, and that its predictions can't be improved by further accumulation of information. This predisposition could be expected to the structure decision to estimate climate dependent on the climate of the previous two days, which might be too short to even think about capturing slants in climate that practical regression requires. On the off chance that the figure were rather founded on the climate of the past four or five days, the predisposition of the practical regression model could probably be decreased. In any case, this would require significantly more calculation time alongside retraining of the weight vector w , so this will be conceded to future work.

Coming to the Logistic Regression, it proved vital to classify whether a day would be rainy or not. Its significance was proven by the accuracy of the results, where it predicted the classification right, more often than not.

Figure 6.1: Logistic Regression Code

```
27 #fitting logistic regression to the training set
28 from sklearn.linear_model import LogisticRegression
29 classifier = LogisticRegression(random_state=0)
30 classifier.fit(X_train, y_train)
31
32 #predict
33 y_pred=classifier.predict(X_test)
34
35 #confusion matrix
36 from sklearn.metrics import confusion_matrix
37 cn=confusion_matrix(y_test, y_pred)
38
39 from sklearn.metrics import classification_report
40 print(classification_report(y_test,y_pred))
```

Talking about Random Forest Regression, it proves to be the most accurate regression model. Likely so, it is the most popular regression model used, since it is highly accurate and versatile. Below is a snapshot of the implementation of Random Forest in the project code:

```
10
17 #random Forest
18 from sklearn.ensemble import RandomForestRegressor
19 regressor = RandomForestRegressor(n_estimators=500,random_state=0)
20 regressor.fit(X,y)
21 y_pred=regressor.predict(X)
```

Figure 6.2: Random Forest Regression code.

ANN with backpropagation utilizes an iterative procedure of preparing where, it more than once contrasts the watched yield and focused on yield and computes the mistake. This blunder is utilized to rearrange the estimations of loads and predisposition to show signs of improvement yield. Subsequently this technique attempts to limit the blunder. In this manner, Artificial Neural system with Backpropagation algorithm is by all accounts most fitting strategy for estimating climate precisely.

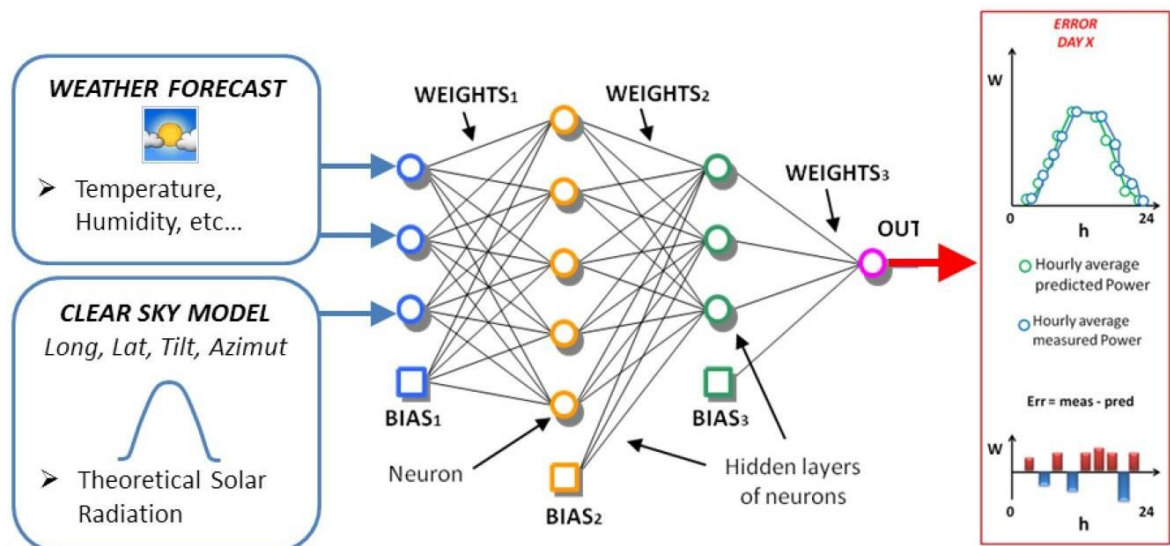


Figure 6.3: Diagrammatic representation of weather prediction using ANN.

The climate Forecasting has a major test of foreseeing the precise outcomes which are utilized in numerous ongoing frameworks like power offices, air terminals, the travel industry focuses, and so forth. The trouble of this determining is the mind boggling nature of parameters. Every parameter has an alternate arrangement of scopes of qualities. This issue is tended to by ANN. It acknowledges every single complex parameter as info and produces the clever examples while preparing and it utilizes similar examples to create the gauges.

REFERENCES

- [1] Mohammad Wahiduzzaman, Eric C. J. Oliver, Simon J Wotherspoon, Neil J. Holbrook, “A climatological model of North Indian Ocean tropical cyclone genesis, tracks and landfall”.
- [2] Jinglin Du, Yayun Liu , Yanan Yu and Weilan Yan, “A Prediction of Precipitation Data Based on Support Vector Machine and Particle Swarm Optimization (PSO-SVM) Algorithms”
- [3] Prashant Kumar, Atul K. Varma, “ Atmospheric and Oceanic Sciences Group, EPSA, Space Applications Centre (ISRO), Ahmedabad, IndiaAssimilation of INSAT-3D hydro-estimator method retrieved rainfall for short-range weather prediction”
- [4] Prashant Kumar, C. M. Kishtawal, P. K. Pal, “Impact of ECMWF, NCEP, and NCMRWF global model analysis on the WRF model forecast over Indian Region”
- [5] H. Vathsala, Shashidhar G. KoolagudiPrediction, “Model for peninsular Indian summer monsoon rainfall using data mining and statistical approaches”
- [6] Mark Holmstrom, Dylan Liu, Christopher Vo, “Machine Learning applied to weather forecasting”, Stanford University, 2016.
- [7] Gyanesh Shrivastava, Sanjeev Karmakar, Manoj Kumar Kowar, “ Application of Artificial Neural Networks in Weather Forecasting: A Comprehensive Literature Review”, International Journal of Computer Application, 2012.
- [8] Meera Narvekar, Priyanca Fargose, “Daily weather forecasting using Artificial Neural Network”, International Journal of Computer Application, 2015.