WEATHER PREDICTION USING MACHINE LEARNING TECHNIQUES

Souri Satya Saketh Ravi, Amaan Sajid Shaik, Abhi, Rahul Katinni, Sai Praneet Reddy Chinthala

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 consider 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 pf scienceand 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 gave 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 does'nt 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 ¾ size of information is utilized and ¼ 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.

Once the model is trained, we can test our data by applying our algorithms on the Test Data. With the help of this we can find the learning ability of our algorithm

ALGORITHMS

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

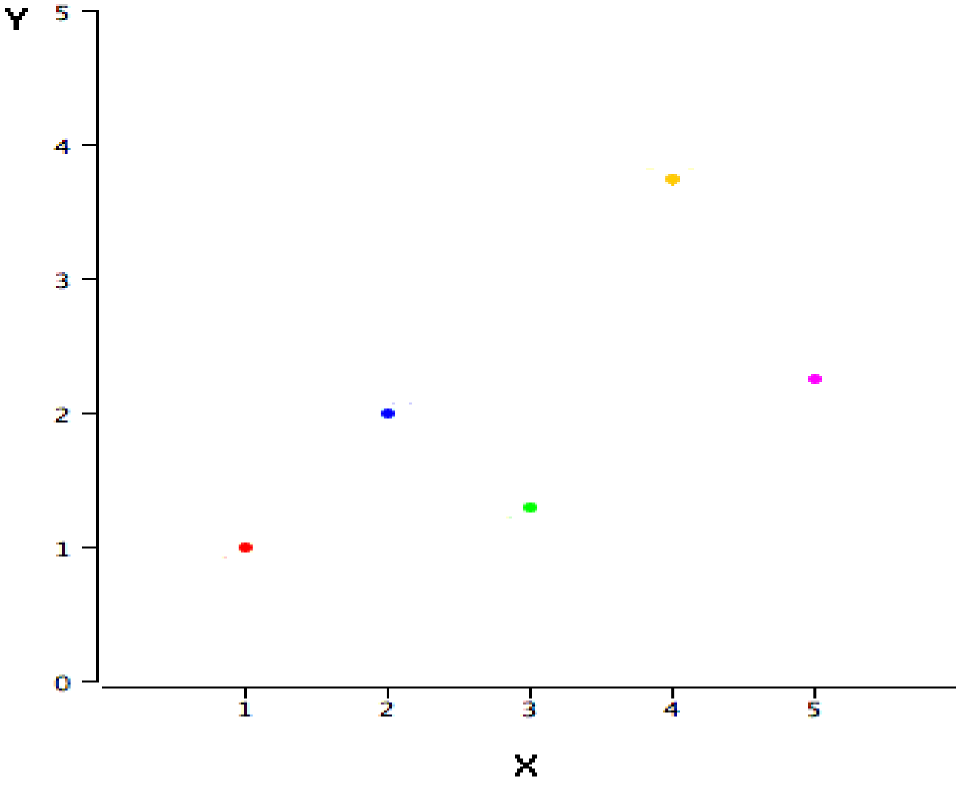


Figure 1.Scatter Graph of information.

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.

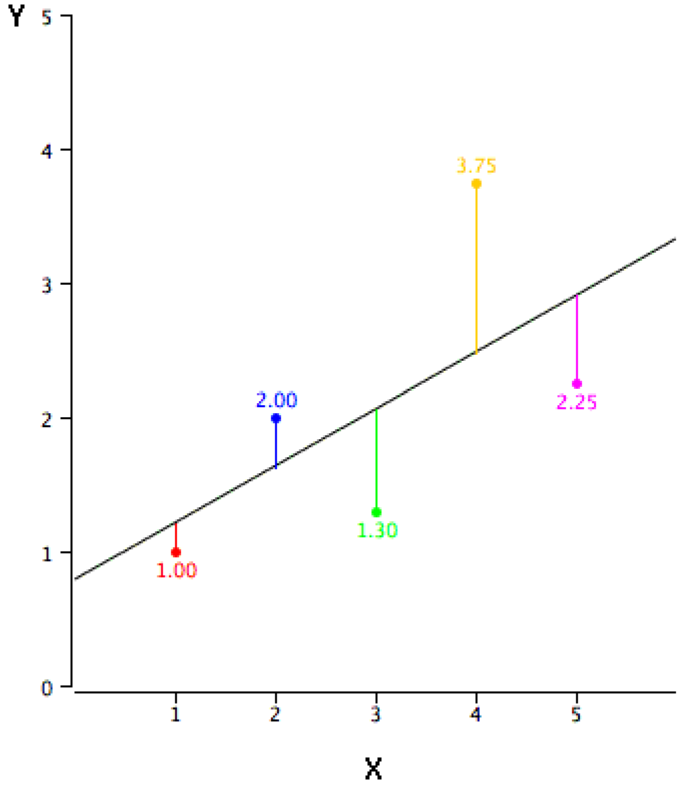


Figure 2. A scatter graph of the data with regression line.

The regression line is used for preditions 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 thecomparisionoferror

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 0.36.

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 If X = 1,

Y' =1.21. If X = 2, Y' = 1.64.

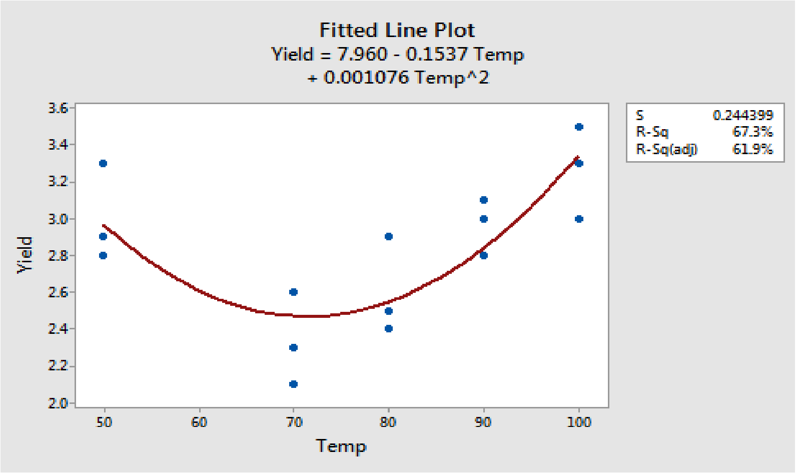
Polynomial Linear Regression

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=β0+β1X+β2X2+…+βhXh+ϵ,

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, β1,β2,...,βh.

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.

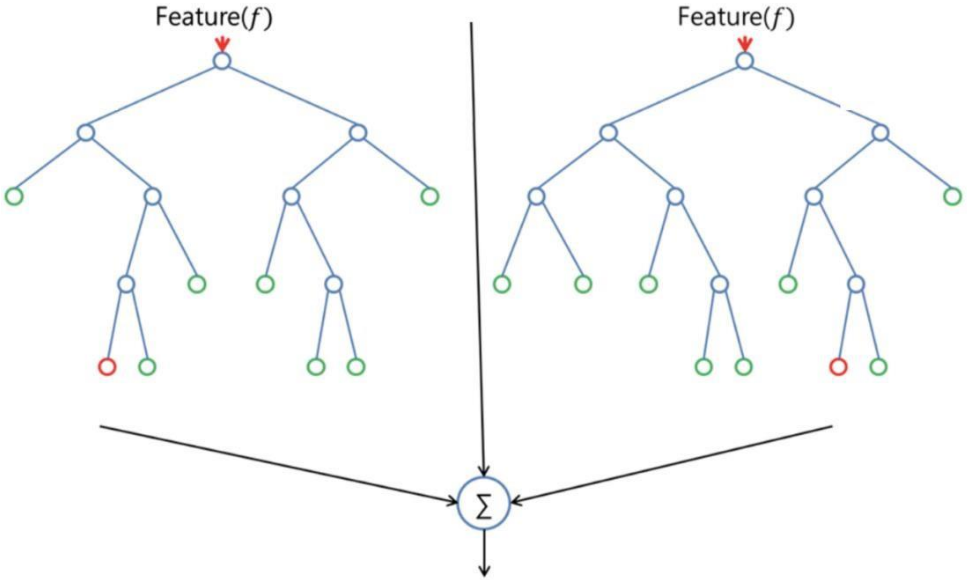
Random Forest Regression

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 << 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.

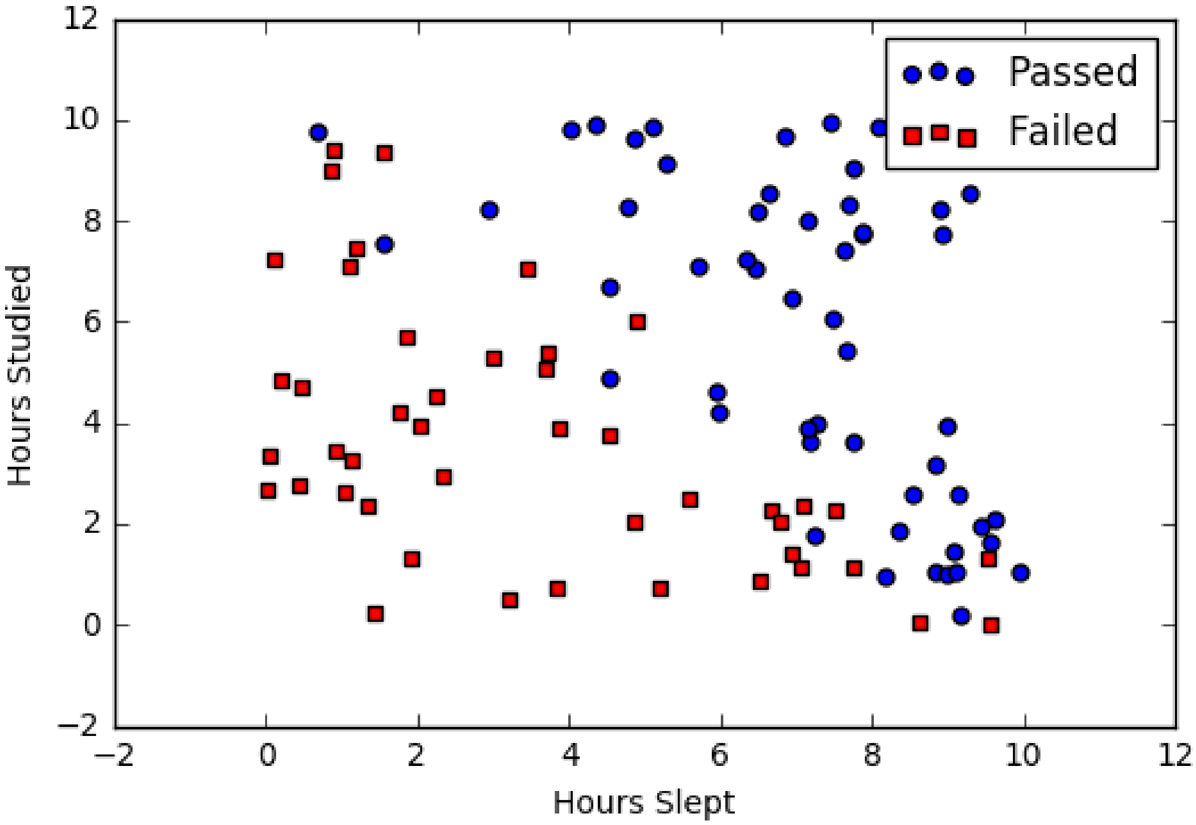
iv) Repeat all the steps from a to c until “l” number of nodes has been finally reached.

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

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.

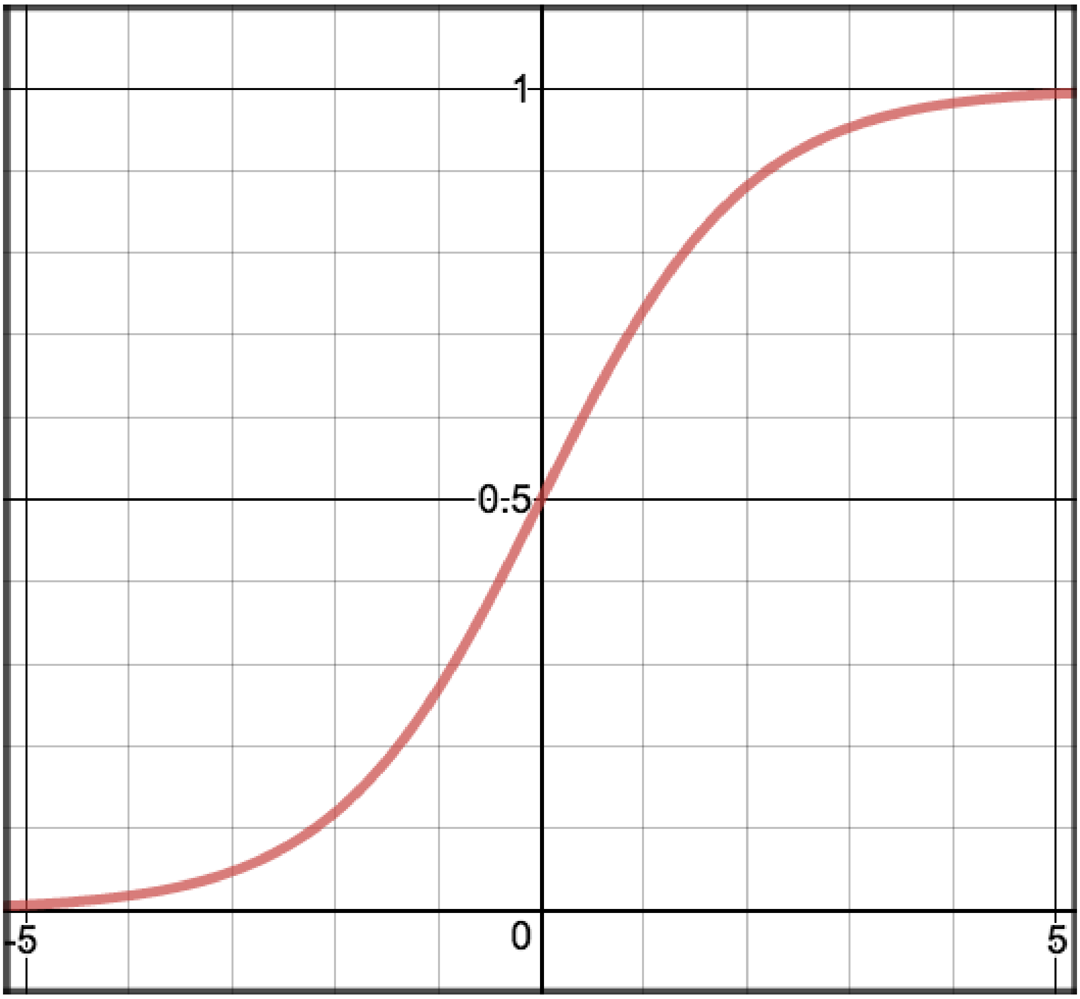
Let's assume we're given information on understudy test results and our objective is to foresee whether an understudy will pass or fall flat dependent on number of hours dozed and hours spent considering. We have two highlights (hours rested, hours contemplated) and two classes: passed (1) and fizzled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



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.

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



Graph: Sigmoid Function

4.1 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 nonstraight 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 it existence between (0 to1). 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 aslo 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

PERFORMANCE ANALYSIS

5.1 Dataset

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:

Date and time	Precipitatio n	Atmospheric pressure	Humidity	Fog	Temperature
18-11-1996 11:00	0	934	2	0	18
18-11-1996	0	936	3	0	19

12:00					
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

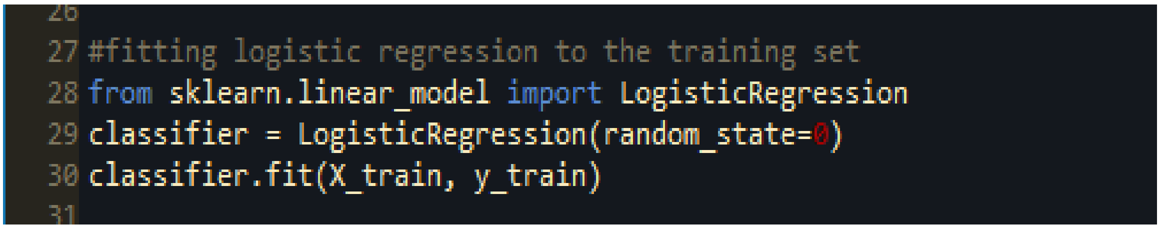
5.2 Test Metrics

5.2.1 Scikit-Learn library in Python

Scikit-learn is a free machine learning library for Python. It highlights different algorithms like support vector machine, random forests, and k-neighbors, and it likewise underpins Python numerical and scientific libraries like NumPy and SciPy.

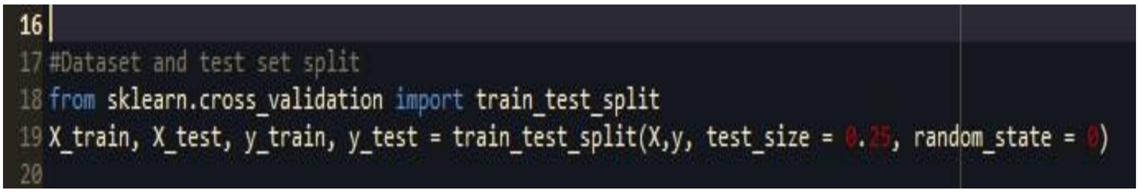
The library has functions like accuracy_score(), RandomForestRegressor() and many other very useful regression functions that enable us to make accurate predictions.

Given below is a snapshot of the use of the library in the code.



```
#fitting logistic regression to the training set
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state=0)
classifier.fit(X_train, y_train)
```

Figure: Implementation of Scikit-Learn Library for Logistic Regression



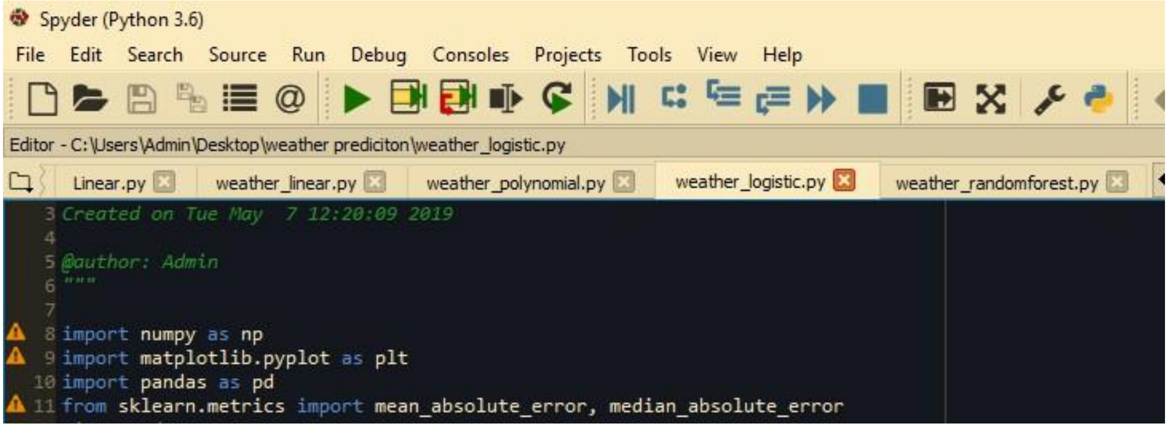
```
#Dataset and test set split
from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.25, random_state = 0)
```

Figure: Implementation of Scikit-learn to split dataset into test set and train set

5.2.2 Pandas

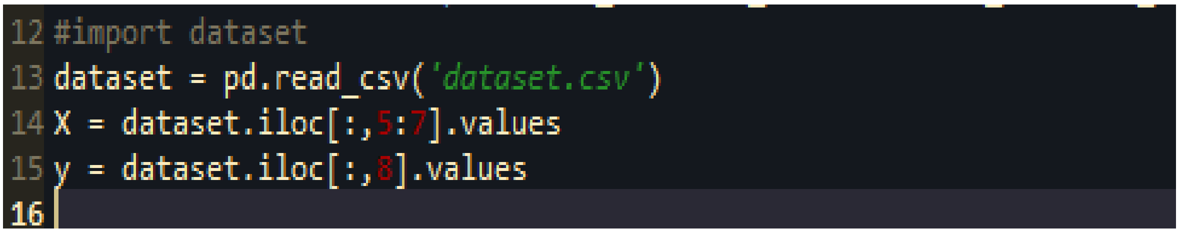
Pandas is an open source, BSD-authorized library giving superior, simple to-utilize information structures and information investigation apparatuses for the Python programming language.

Pandas has been heavily utilized in the development of this project. Given below are a few snapshots from the code.


Spyder (Python 3.6)
File Edit Search Source Run Debug Consoles Projects Tools View Help
Editor - C:\Users\Admin\Desktop\weather prediciton\weather_logistic.py
Linear.py
weather_linear.py
weather_polynomial.py
weather_logistic.py
weather_randomforest.py

```
Created on Tue May  7 12:20:09 2019

@author: Admin
"""

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.metrics import mean_absolute_error, median_absolute_error
```

Figure: Pandas being imported to be used in the code



```
#import dataset
dataset = pd.read_csv('dataset.csv')
X = dataset.iloc[:,5:7].values
y = dataset.iloc[:,8].values

```

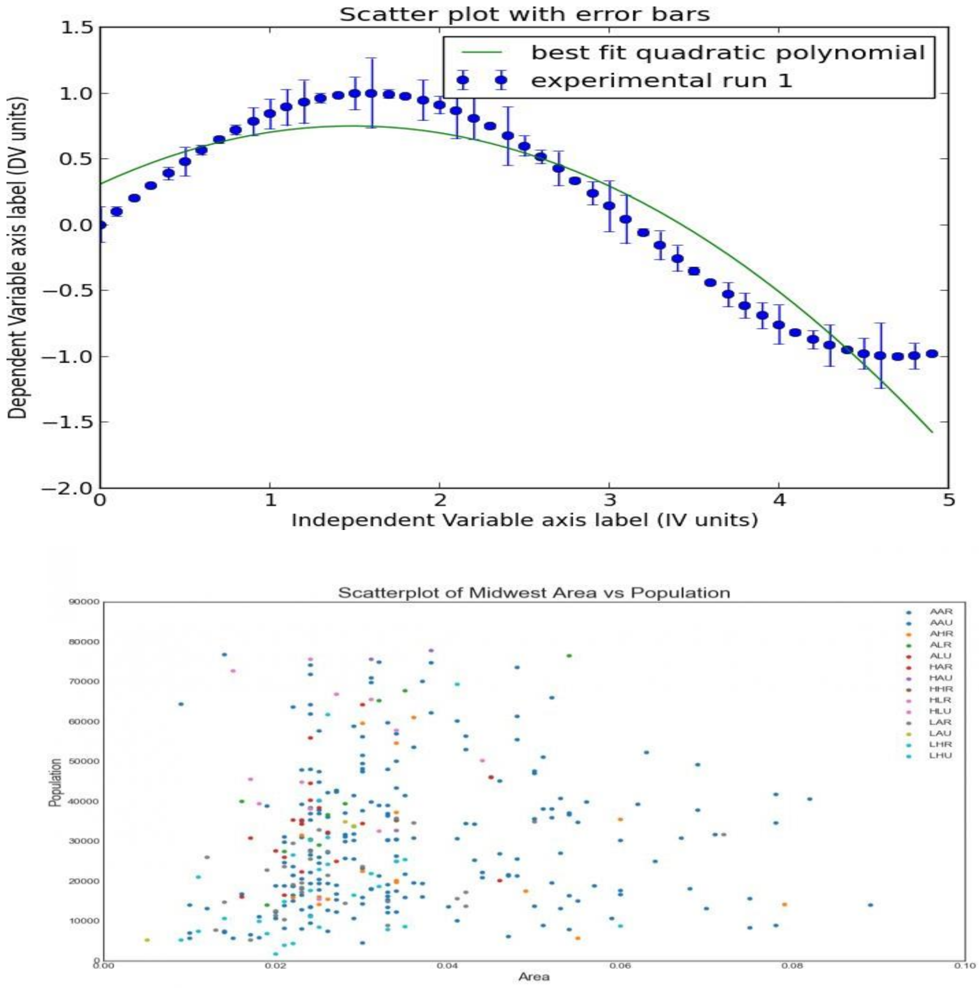
Figure: Using the Pandas object to import the dataset

5.2.3 Matplot Library

Matplotlib is a plotting library for the Python programming language and its numerical science expansion NumPy. It gives an item situated API to implanting plots into applications utilizing broadly useful GUI toolboxs like Tkinter, wxPython, Qt, or GTK+. There is additionally a procedural "pylab" interface dependent on a state machine (like OpenGL), intended to intently look like that of MATLAB, however its utilization is discouraged. SciPy utilizes Matplotlib.

Matplotlib was initially composed by John D. Seeker, has a functioning improvement community, and is circulated under a BSD-style permit. Michael Droettboom was selected as matplotlib's lead designer presently before John Hunter's demise in August 2012, and further joined by Thomas Caswell.

Following are the examples of graphs that can be plotted using the matplot library: Figure: Types of graphs plotted using matplot library



5.2.1 Confusion Matrix

A confusion matrix is a procedure which abridges the execution of an order calculation. It is a synopsis of forecast results on a characterization issue. Characterization precision can be deceiving there are an unequal number of perceptions in each class or if there are in excess of two classes in the dataset. Ascertaining a disarray lattice gives a superior thought of what the characterization demonstrate is getting right and the sorts of blunders it is making.

The quantity of off base forecasts and right expectations are outlined with check esteems and are separated by each class. This goes about as the way to the disarray grid. The manners by which the order display is befuddled when it makes forecasts is appeared by the disarray lattice. It gives an understanding into the mistakes being made by your classifier. It is this breakdown that conquers the restriction of utilizing characterization exactness alone.

Calculation of Confusion Matrix

The method for computing a confusion matrix is demonstrated as follows.

An arrangement of test information or an approval informational index is required with the normal outcome esteems. The forecast is made for each line in the test informational collection. From the normal outcomes and conjectures, coming up next are considered: The quantity of erroneous estimates for every classification. The quantity of right expectations for each class sorted out by the class gave. These numbers are sorted out into a table as pursues:

It is normal from the side: each line of the framework compares to an anticipated class. Forecast at the best: Each section of the table relates to a genuine class. Right and off base grouping numbers are finished in the table. The line esteem is normal for this class and the anticipated section an incentive for this class is loaded up with the aggregate number of right forecasts for a class.

Additionally, the request expected for that class esteem and the anticipated an incentive for this segment class is loaded up with the aggregate number of erroneous expectations for a class. Practically speaking, a parallel classifier like this can complete two kinds of mistakes: it is erroneously credited to a man who has not showed up in the predefined classification or is wrongly ascribed to a man who has not showed up in the predefined class. Deciding these two sorts of blunders is frequently a region of intrigue. A disarray framework is an advantageous method to show this kind of data.

This grid can without much of a stretch be utilized for issues in two classes where it is straightforward, however it can likewise be connected to issues with at least 3 class esteems, adding more lines and segments to network perplexity.

Accuracy

Accuracy is one of the measures to evaluate classification models. The precision is the fraction of the predictions given by the classification model. The precision has the following definition: Accuracy = Total no. of the correct forecasts / From predictions

For the binary classification, the accuracy can be calculated as negative and positive in the following way:

Accuracy=((TP+TN)/(TP+TN+FP+FN))

TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

Table 5.2 Representation of Confusion Matrix

	Predicted Value	**Predicted Value**
Real Value	True Positive(TP) Reality: Rain ML model predicted: Rain	False Positive(FP) Reality: No Rain ML model predicted: Rain
Real Value	False Negative(FN) Reality: Rain ML model predicted: No Rain	True Negative(TN) Reality: Benign ML model predicted: No Rain

Precision

The precision determines how often it is correct when the model predicts positive. Accuracy helps determine when the cost of false positives is high.

Precision = TP / (TP + FP)

where TP is the number of real positives and FP the number of false positives. Precision refers to the ability of the classifier not to designate a positive sample as negative.

Recall

Recall it helps to determine how much the false negative cost is. Recall = TP / (TP + FN)

Where TP is true positive and the number of FN is false negative number. Recall refers to the classification capability to find all the classified samples.

F1 Score

F1 is a measure of purity of the test. It checks both accuracy and memory. This is considered right when F1 score is 1 and there is a total failure of 0.

F1 = 2 * (Precision * Recall) / (Precision + Recall)

5.3 Test Setup

The test process is already in-built in our system. The testing process taking place just after the model is trained. After the completion of the training process, we analyze each data entry in the test set. In order to analyze each entry, we use descriptors to extract features. Now we compare these feature values with the feature values which were initially retained using the train set. The comparison is done according to the Machine Learning model used and finally the output for each entry is received. Since each data entry is already labeled, we can compute accuracy by comparing the predicted value with the received values.

5.4 Result

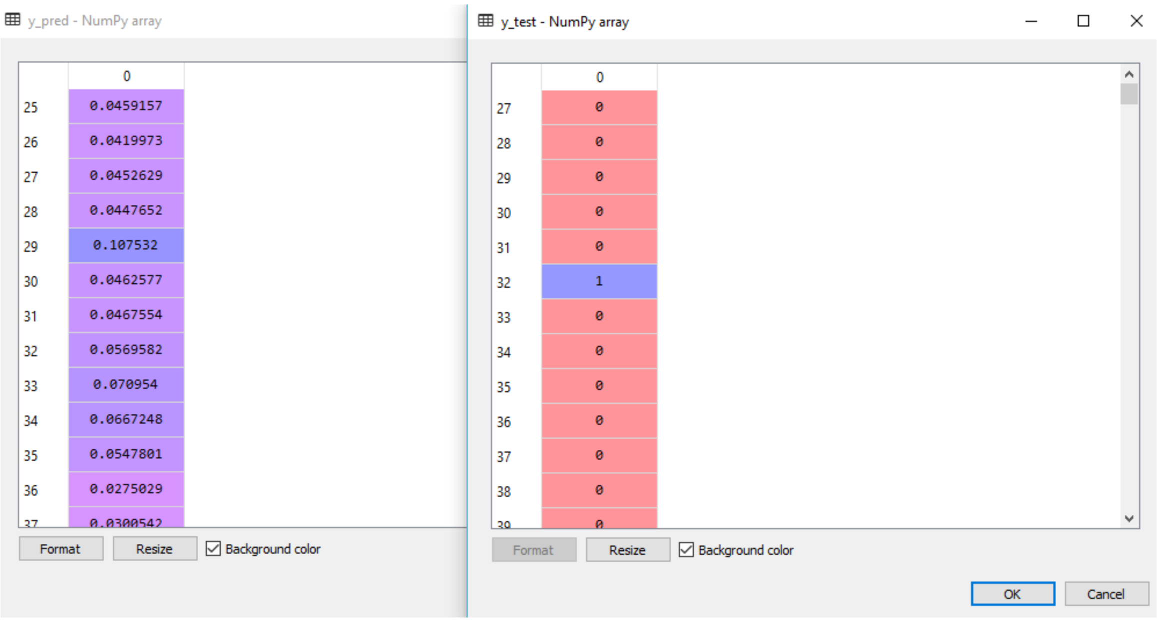
The results of the implementation of the project are demonstrated below.

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



y_pred - NumPy array

	0
25	0.0459157
26	0.0419973
27	0.0452629
28	0.0447652
29	0.107532
30	0.0462577
31	0.0467554
32	0.0569582
33	0.070954
34	0.0667248
35	0.0547801
36	0.0275029
37	0.0300542

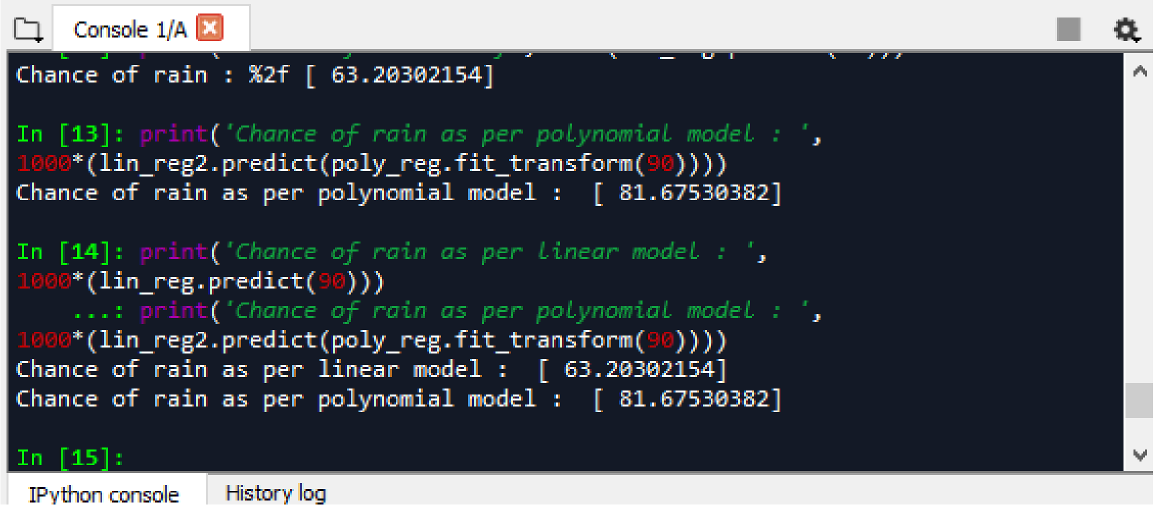
y_test - NumPy array

	0
27	0
28	0
29	0
30	0
31	0
32	1
33	0
34	0
35	0
36	0
37	0
38	0
39	0

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 that linear regression. Below is a snapshot of its implementation in the code, and the result it displayed.



```
Chance of rain : %2f [ 63.20302154]

In [13]: print('Chance of rain as per polynomial model : ',
1000*(lin_reg2.predict(poly_reg.fit_transform(90))))
Chance of rain as per polynomial model :  [ 81.67530382]

In [14]: print('Chance of rain as per linear model : ',
1000*(lin_reg.predict(90)))
    ...: print('Chance of rain as per polynomial model : ',
1000*(lin_reg2.predict(poly_reg.fit_transform(90))))
Chance of rain as per linear model :  [ 63.20302154]
Chance of rain as per polynomial model :  [ 81.67530382]

In [15]:
```

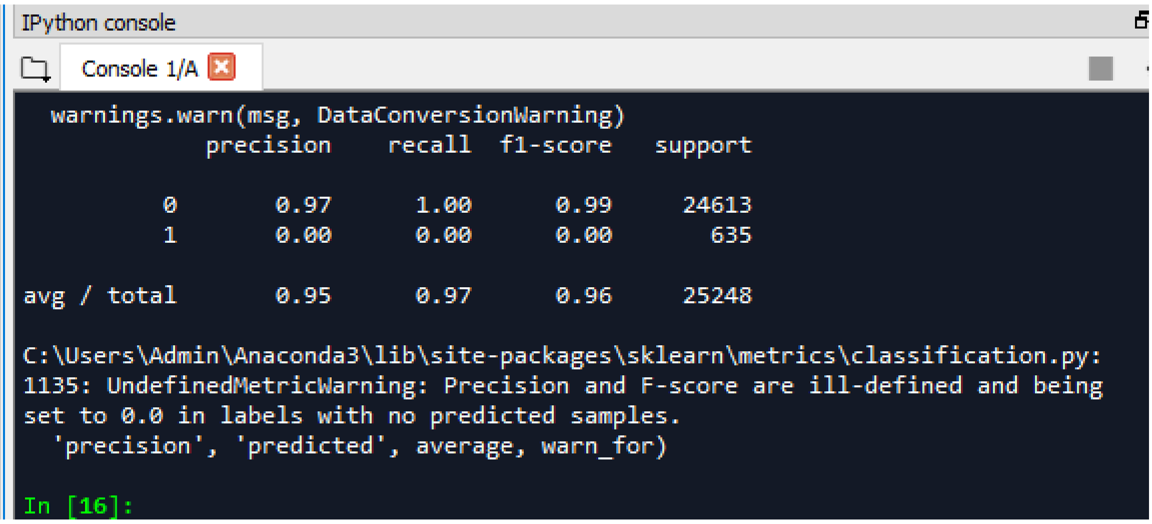
Figure 5.4.2: Comparison of results from linear regression and Polynomial regression

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.



```
  warnings.warn(msg, DataConversionWarning)
             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

C:\Users\Admin\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:
1135: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)

In [16]:
```

Figure 5.4.3: Confusion matrix for Logistic Regression.

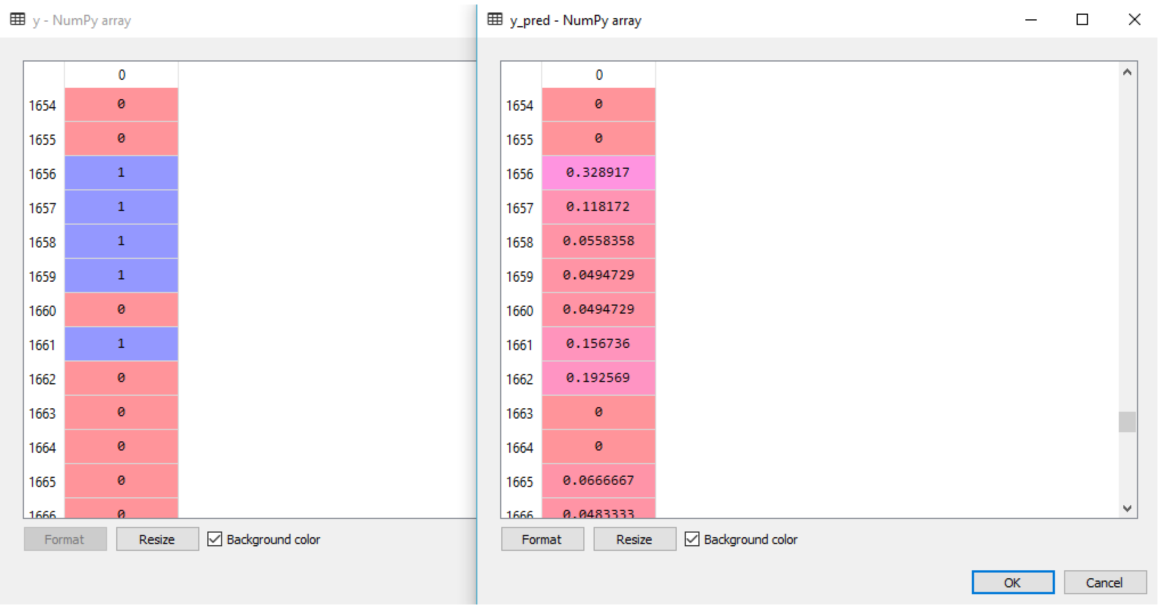
	Precision	Recall	F1-score	Support
0	0.97	1.00	0.99	24613
1	0.00	0.00	0.00	635
Avg/total	0.95	0.97	0.96	25248

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.



y - NumPy array

	0
1654	0
1655	0
1656	1
1657	1
1658	1
1659	1
1660	0
1661	1
1662	0
1663	0
1664	0
1665	0
1666	0

y_pred - NumPy array

	0
1654	0
1655	0
1656	0.328917
1657	0.118172
1658	0.0558358
1659	0.0494729
1660	0.0494729
1661	0.156736
1662	0.192569
1663	0
1664	0
1665	0.0666667
1666	0.0483333

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.

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.

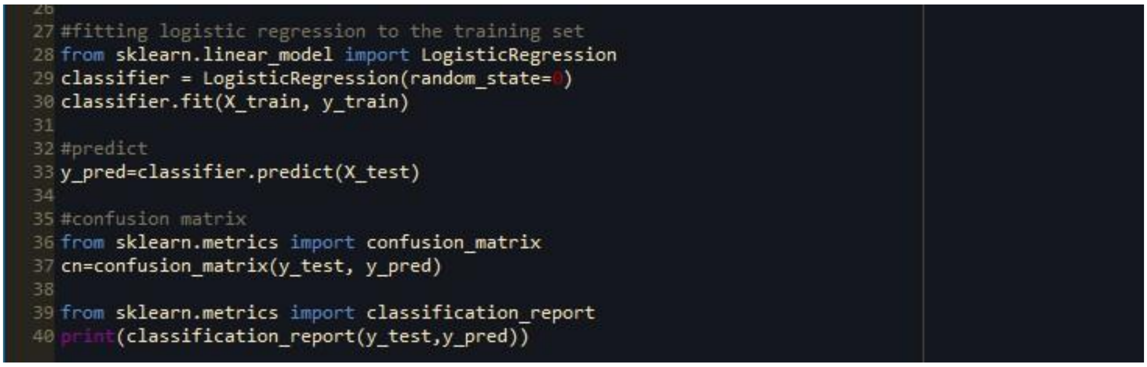
Linear regression demonstrated to be a low predisposition, high fluctuation model though polynomial regression demonstrated to be a high predisposition, low difference model.

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.

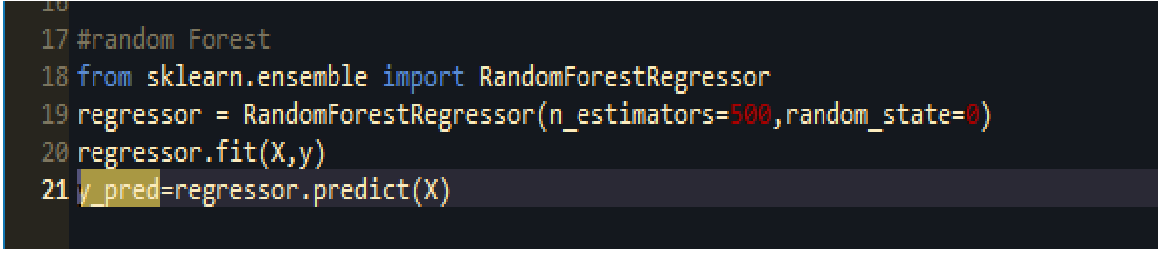
Figure 6.1: Logistic Regression Code



```
#fitting logistic regression to the training set
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state=0)
classifier.fit(X_train, y_train)

#predict
y_pred=classifier.predict(X_test)

#confusion matrix
from sklearn.metrics import confusion_matrix
cn=confusion_matrix(y_test, y_pred)

from sklearn.metrics import classification_report
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:

Figure 6.2: Random Forest Regression code.



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

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.

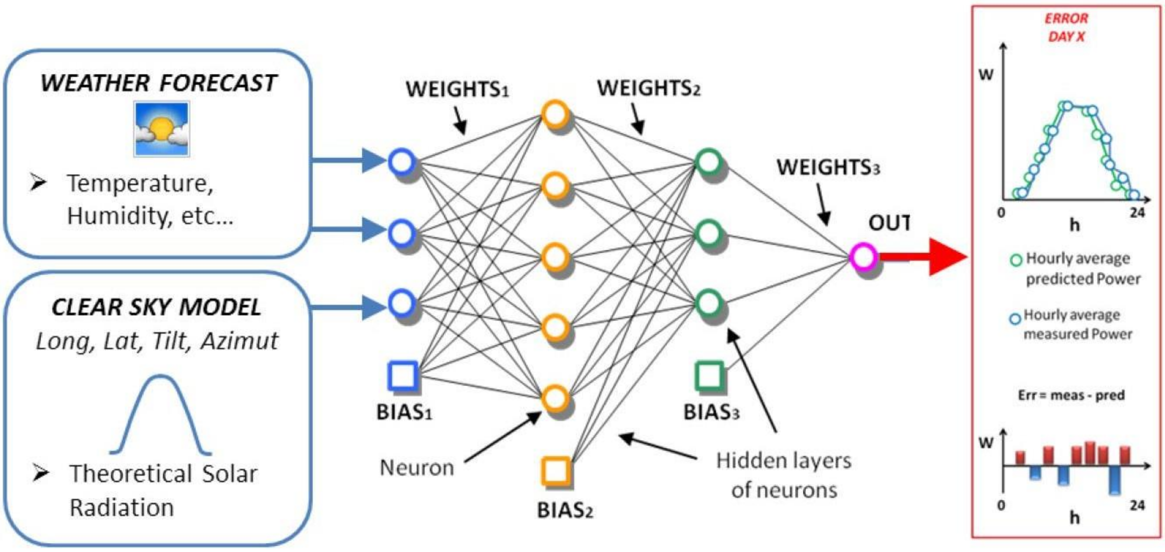


Figure 6.3: Diagrammatic representation of weather prediction using ANN.

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.

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