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Long Term Temperature Forecasting using Regression Model

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Abstract

Air temperature is an essential climatic component. Due to the ever-changing weather conditions, prediction has become a challenging task. The main motive of this research work is to work on long term prediction of maximum temperature for various stations of Pokhara. This work explores machine learning algorithm linear regression for Time Series data. Various visualization of data were observed which helped in implementing the approaches of prediction. For given stations the expected maximum temperature in each month and in whole of the year is predicted here. Also, for given maximum temperature in previous three months, the prediction of maximum temperature in rest month is done and is validated. Statistical Linear regression and Linear regression with Elastic net and hyperparameter are used. For analysis Mean Absolute Difference (MAD) for Training data and Testing data for various cases are observed. The correlation between predicted and actual data is shown using Mean and Standard Deviation. The result of the analysis states that regression based maximum temperature long term prediction models provide better accuracy with lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Keywords: *Maximum Temperature, Linear Regression, Long term prediction, MAD, MAE, RMSE*

1. Introduction

Weather prediction is a complex process and a challenging task for researchers. It includes expertise in multiple disciplines [1], [2]. The prediction of atmospheric parameters is essential for various applications. Some of them include climate monitoring, drought detection, severe weather prediction, agriculture and production, planning in energy industry, aviation industry, communication, pollution dispersal [5] etc. Accurate prediction of weather parameters is a difficult task due to the dynamic nature of atmosphere. Various techniques like linear regression, auto regression etc. to predict atmospheric parameters like temperature, wind speed, rainfall, meteorological

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pollution etc. [3-8].

In general, weather forecasting, which is a task to predict the conditions of the atmosphere for a given location and time, is an interesting computer vision problem with wide potential applications. Despite many models have been proposed, weather forecasting based on ground-based observation data remains a challenging task. According to studies by Baklanov et al. [9] and Maunder J. RW Katz and AH Murphy [10], the main challenge of weather forecasting is due to the fact that weather condition is the result of a complex process which is quite difficult to formulate in single mathematical model. In the limited scope, many researches have attempted to build weather forecasting models using statistical methods to predict weather using single or multiple variables as predictors.

The high popularity of machine learning and deep learning methods in the past ten years have motivated many researchers to propose such methods for weather forecasting tasks. For example: neural network or NN [11].

Nepal, being a developing nation where 60% of the entire population is involved in agriculture, has a disproportionate dependence on traditional fuels [12]. According to the Department of Hydrology and Meteorology (DHM), only 284 meteorological stations are currently in operation in Nepal. Although empirical models are widely analyzed and evaluated, the performance of these models is found to vary according to the geographical location and local climate [13]. Lately, several machine learning (ML) models are employed to estimate GSR at several locations [14-15] capability of generalizing and optimizing time and capacity to resolve problems that are difficult to be represented by an explicit algorithm are some of the biggest advantages of ML models [16-17].

Regression analysis have been used effectively to answer many questions in the way we handle system modeling and advance associations between problem variables. It is important to develop such a relationship between variables in many cases such as predicting stock market [18-21]. It is important to understand how stock index move over time.

1.1. Single Linear Regression

In order to understand how linear regression works, assume we have n pairs of observations dataset {xi, yj} i=1...,n as given in Figure 1. Our objective is to develop a simple relationship between the two variables x (i.e. input variable) and y (i.e output variable) so that we can develop a line equation (see Equation 1).

$$y = a + bx \tag{1}$$

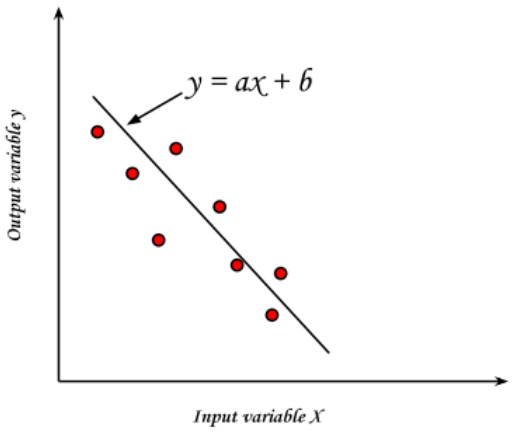


Figure 1: Simple linear model

where a is a constant (i.e. bias) and b is the slope of the line. It is more likely that the straight line will not pass by all the points in the graph. Thus, Equation 1 shall be re-written as follows:

$$y = a + bx + \varepsilon \quad (2)$$

where ε represents the error difference between the values of x_i and y_i at any sample i. Thus, to find the best line that produce the most accurate relationship between x and y. We have to formulate the problem as an optimization problem such that we can search and find the best values of the parameters (i.e. $\hat{a}$ and $\hat{b}$). In this case, we need to solve an error minimization problem. To minimize the sum of the error over the whole data set. We need to minimize the function L given in Equation 3.

$$L = \sum_{i=1}^{n} \epsilon_i^2 = \sum_{i=1}^{n} (y_i - a - bx_i)^2 \quad (2)$$

To find the optimal values for $\hat{a}$ and $\hat{b}$ we have to differentiate L with respect to a and b.

$$\frac{\partial L}{\partial \hat{a}} = -2 \sum_{i=1}^{n} (y_i - \hat{a} - \hat{b}x_i)$$

$$\frac{\partial L}{\partial \hat{b}} = -2 \sum_{i=1}^{n} (y_i - \hat{a} - \hat{b}x_i)\, x_i \quad (3)$$

By simplification of Equations 4, we get to the following two equations:

$$n\hat{a} + \sum_{i=1}^{n} x_i\, \hat{b} = \sum_{i=1}^{n} y_i$$

$$\sum_{i=1}^{n} x_i\, \hat{a} + \sum_{i=1}^{n} {x_i}^2\, \hat{b} = \sum_{i=1}^{n} x_i y_i \quad (4)$$

Equations 5 is called least square (LS) normal equations. The solution of these normal equations produces the least square estimate for $\hat{a}$ and $\hat{b}$.

2. Literature Survey

Mathew et al. (2016) have presented the concept of Linear Time Series model (LST) which is used to predict the temperature of Jaipur city. They have further pressed on the fact that urbanization is one of the major leading factors affecting the ecosystem [22]. Sharma & Sisodia, (2014) have illustrated the use of fuzzy time series in temperature prediction. They have specified that the length of intervals is important to the fact that it can affect the forecasting accuracy rate [23]. Kavitha et al. (2016) have explained in depth the wide use and importance of linear regression model. They have showcased the accuracy of regression model over the time series analysis, since the former takes into account the dependent factors [24]. Shen et al. (2016) have presented in their paper that linear regression is very accurate in predicting the usefulness of reviews with Yelp as an example. They have thus proved the accuracy and usefulness of regression analysis in various fields including e-commerce [25]. Arjun et al. (2014) have presented the upper hand of multivariate regression since it takes into account multiple dependent factors. They have used the multivariate model to predict the wind speeds and obtained accurate results thus proving the model's wide application range and also its accuracy [26].

3. General Methodology

The overall methodology followed in the research are shown in Figure 2. All the important blocks have been listed and the approach performed for each block is explained in the subsequent sections.

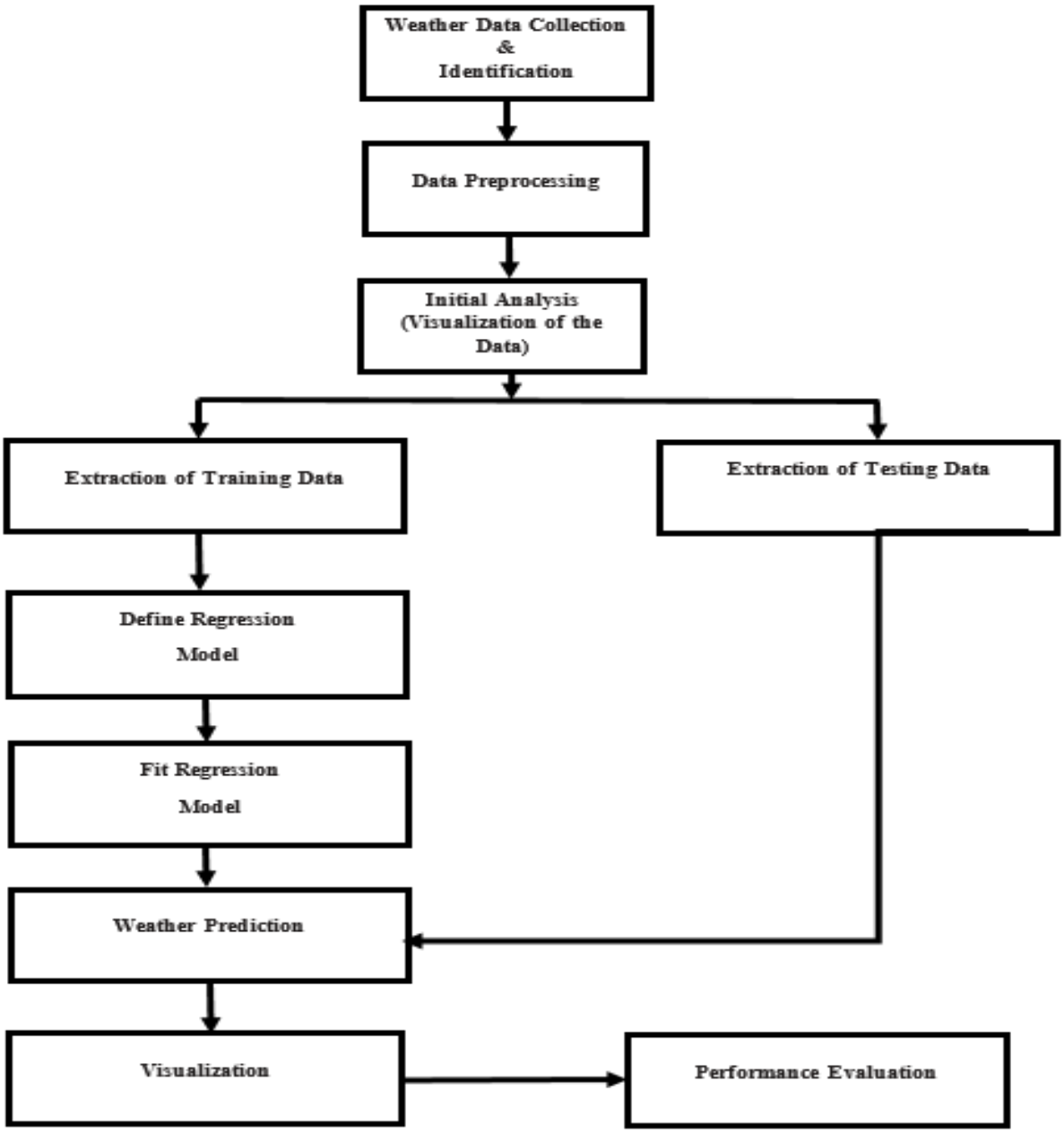


Figure 2: Block diagram of proposed system

In this research long term predictions of weather features are done. Methodology involves following process.

3.1. Weather Data Collection & Identification

The dataset was collected from Department Of Hydrology and Meteorology. Data of weather features rainfall, maximum temperature, minimum temperature and humidity are obtained. The data obtained is on daily basis in .excel file. The dataset obtained is from various stations of Pokhara. Many stations has data available for 1950 to 2020 years.

Maximum Temperature of a day is highest recorded value of temperature in Celsius. For maximum temperature, data obtained is from 26 stations namely 44434Pokhara Airport, 804Pokhara Airport, 811Malepatan(Pokhara), 814Lumle, 842GHALE KHARKA, 851 BEGNAS, 868Panchase, 869Panchase, 870Panchase, 871Panchase, 872Panchase, 873Panchase, 874Panchase, 875Panchase, 876Panchase, 877Panchase, 878Panchase, 879Panchase,

870Jyamirebari, 871Jyamirebari, 872Jyamirebari, 873Jyamirebari, 874Jyamirebari,8 75Jyamirebari, 876Jyamirebari and 877Jyamirebari.

Rainfall of a day is recorded in sum. For rainfall, data obtained is from 17 stations namely 44434Pokhara Airport, 804Pokhara Airport, 811Malepatan(Pokhara), 813Bhadaure Deurali, 814Lumle, 818Lamachaur, 821Ghandruk, 824Siklesh, 829Sallyan(Kaski), 830Pamdur, 842GHALE KHARKA, 843 RIVAN, 849PUMDHI BUMDHI, 851BEGNAS, 854NIRMAL POKHARI, 868Panchase and 870Jyamirebari.

Minimum Temperature of a day is lowest recorded value of temperature in Celsius. For minimum temperature, data obtained is from 8 stations namely 44434Pokhara Airport, 804Pokhara Airport, 811Malepatan(Pokhara), 814Lumle, 842GHALE KHARKA, 851BEGNAS, 868Panchase and 870Jyamirebari.

Relative humidity tells how much water vapor is in the air, compared to how much it could hold at that temperature and is shown as a percent. For relative humidity, data obtained is from 8 stations namely 44434Pokhara Airport, 804Pokhara Airport, 811Malepatan(Pokhara), 814Lumle, 842GHALE KHARKA, 851 BEGNAS, 868Panchase and 870Jyamirebari.

3.2. Dataset Preprocessing

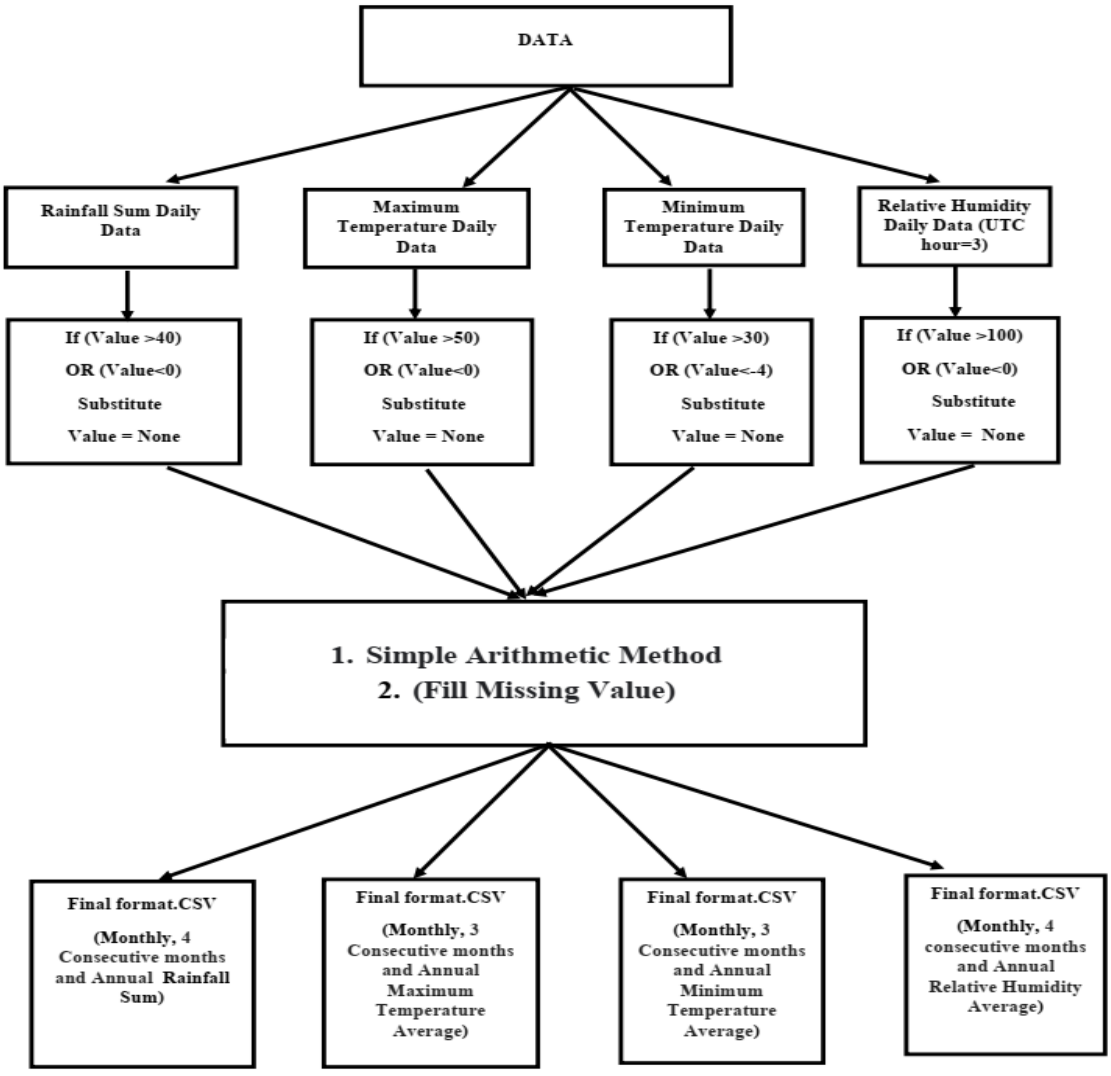


Figure 3: Block diagram data preprocessing

data were also noted to make sure that the data is indeed an anomaly. Abnormally large or small values were substituted as none value. In case of missing data, Simple Arithmetic Method is used. Simple Arithmetic Method takes the data, and fills the null value. Final format of dataset are as follows:

Dataset-1 (Maximum Temperature): Dataset has 26 Stations and 18 attributes (Stations, Year, individual month, combinations of 3 consecutive months, annual). All the attributes have the average value of maximum temperature in degree Celsius.

Dataset-2 (Rainfall Amount): Dataset has 17 Stations and 19 attributes (Stations, Year, individual month, combinations of 4 consecutive months, annual). All the attributes have the sum of amount of rainfall in mm.

Dataset-3 (Minimum Temperature): Dataset has 8 Stations and 18 attributes (Stations, Year, individual month, combinations of 3 consecutive months, annual). All the attributes have the average value of minimum temperature in degree Celsius.

Dataset-4 (Relative Humidity at UTC 3): Dataset has 8 Stations and 19 attributes (Stations, Year, individual month, annual, combinations of 4 consecutive months). All the attributes has the average value of relative humidity in percentage.

For this research work Dataset-1 that is maximum temperature dataset is used.

3.3. Initial Analysis (Visualization of the Data)

The input data visualization is done to understand what kind of data is present. Analysis of the data is done by visualizing the data through a series of plots to gain knowledge of the data. Data analysis involves monthly plots of data, Station wise annual plots, overall average data in each year, average data in each month of year with respect to each station, Heatmap etc.

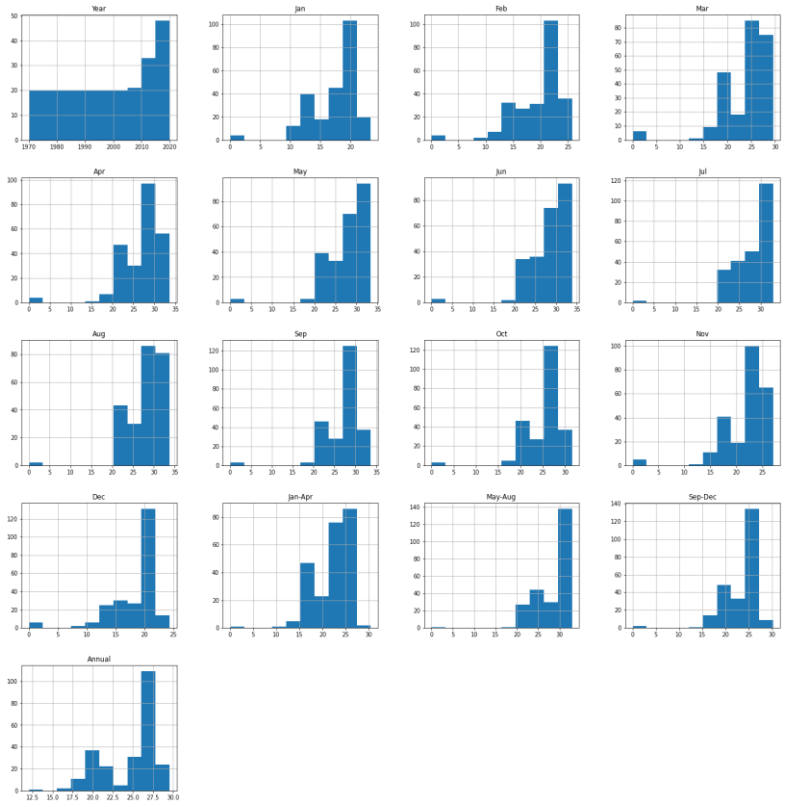


Figure 4: Maximum temperature monthly plot

Figure 4 is histogram plots of maximum temperature for each months in a year, annual plot and overall years plot. For better understanding, plots for three consecutive months are also done. Hence on analyzing Figure 4, it is obtained that the highest amount of maximum temperature is from April to August.

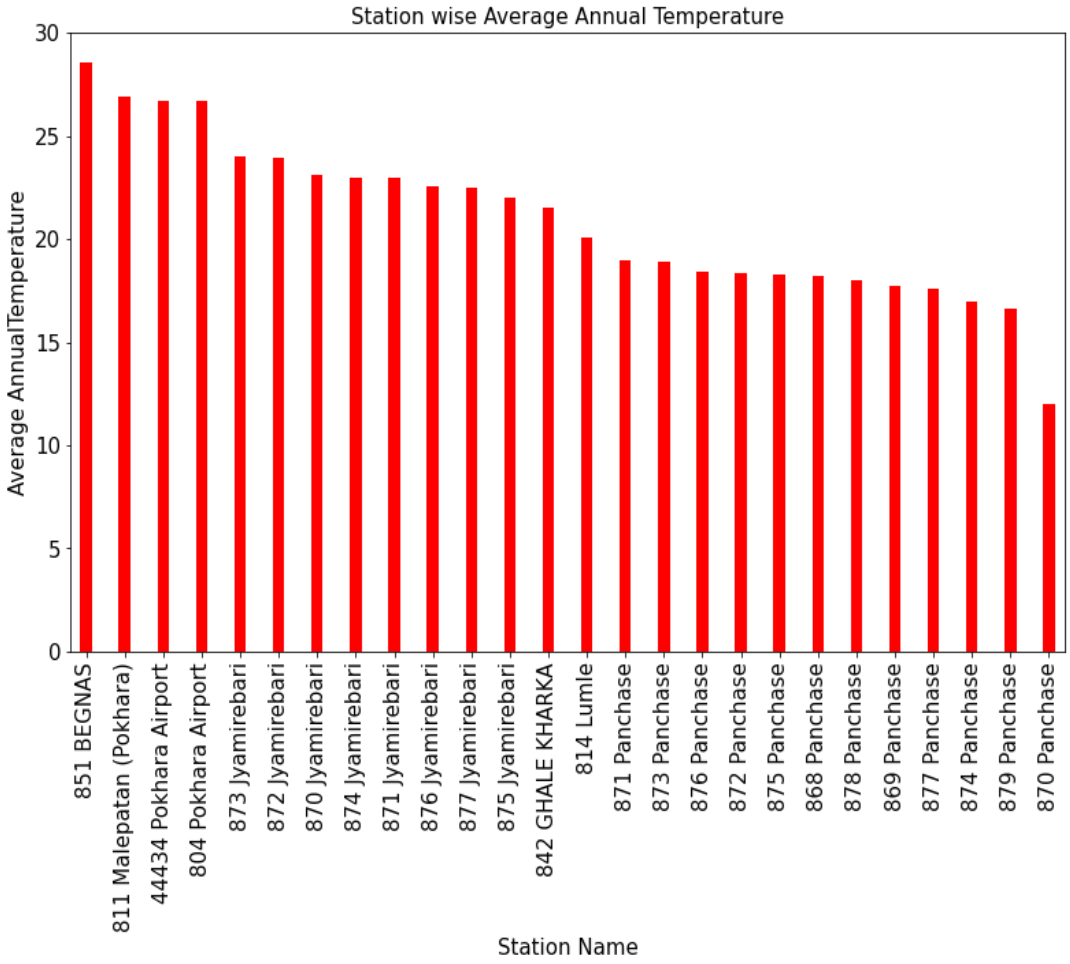


Figure 5: Station wise average annual maximum temperature

Figure 5 shows the average of annual maximum temperature for each station. From Figure 5 relationship can be analyzed. Stations with maximum value and stations with minimum value can obtained from Figure 5. Hence stations with maximum value of average annual maximum temperature are 851BEGNAS with value 28.582379, 811Malepatan (Pokhara) with value 26.895192 and 44434PokharaAirport with value 26.671345 whereas stations with minimum values of annual maximum temperature are 874Panchase with value 16.996552, 879Panchase with value 16.630738 and 870Panchase with value 12.028814.

Figure 6 shows the sum of values for each year from 1970 to 2020. From Figure 6 it is obtained that maximum value of overall maximum temperature (sum of all 26 stations) is 198.50570096 occurred in [2016]. Minimum value of overall maximum temperature (sum of all 26 stations) is 94.680821909999 occurred in [1971] and Average (of all 26 stations) overall maximum temperature (sum of all 26 stations) Mean value is 117.17059556686273.

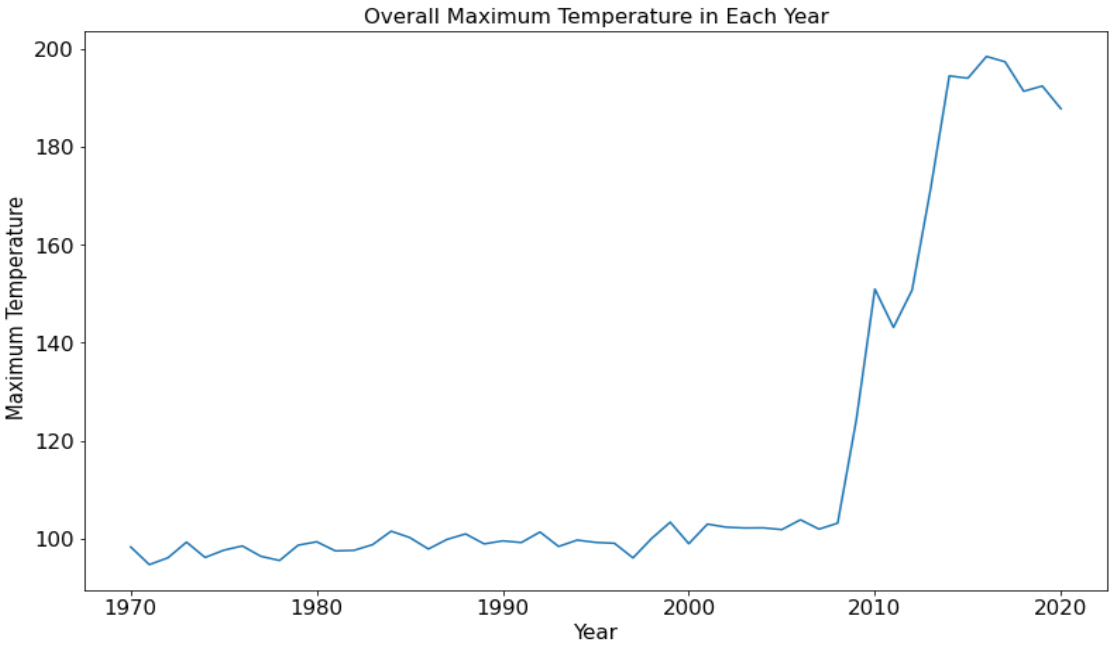


Figure 6: Overall maximum temperature in each year

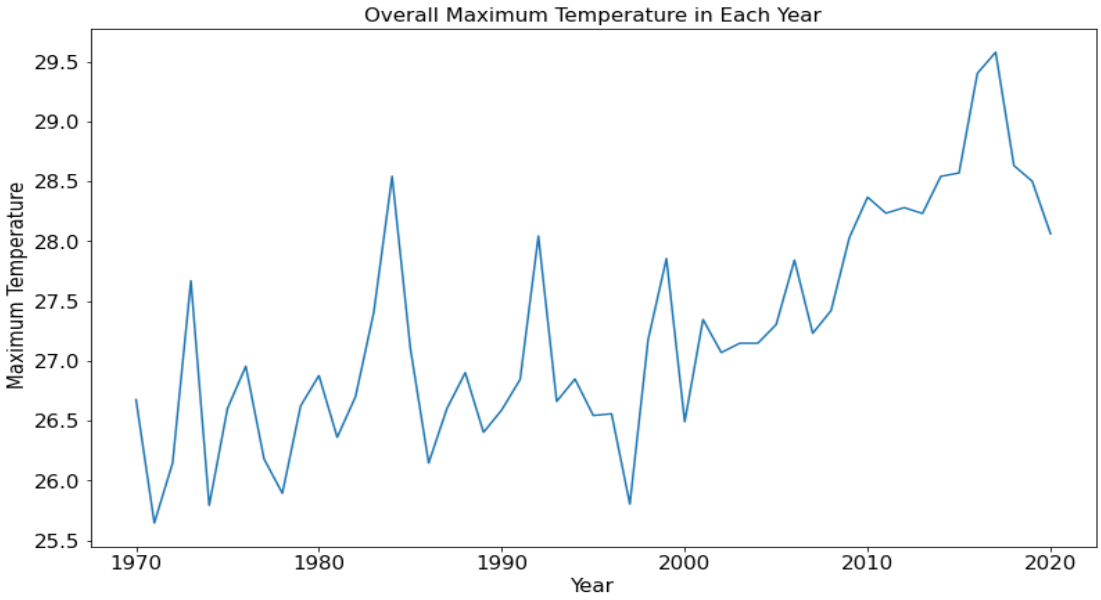


Figure 7: Average of maximum temperature in each year

Figure 7 shows the average of maximum temperature for each year from 1970 to 2020. Hence Maximum value (average of all 26 stations) of maximum temperature obtained is 29.57972603 occurred in [2017], Minimum value (average of all 26 stations) of maximum temperature is 25.64438356 occurred in [1971] and Mean value is 27.246738417843137.

Figure 8 shows plots for each month in a year and for every year from 1970 to 2020. Figure 8 is used for monthly analysis of maximum temperature for each year individually. Hence, it is obtained that in month April, May, Jun, July value is high and in month November, December value is low.

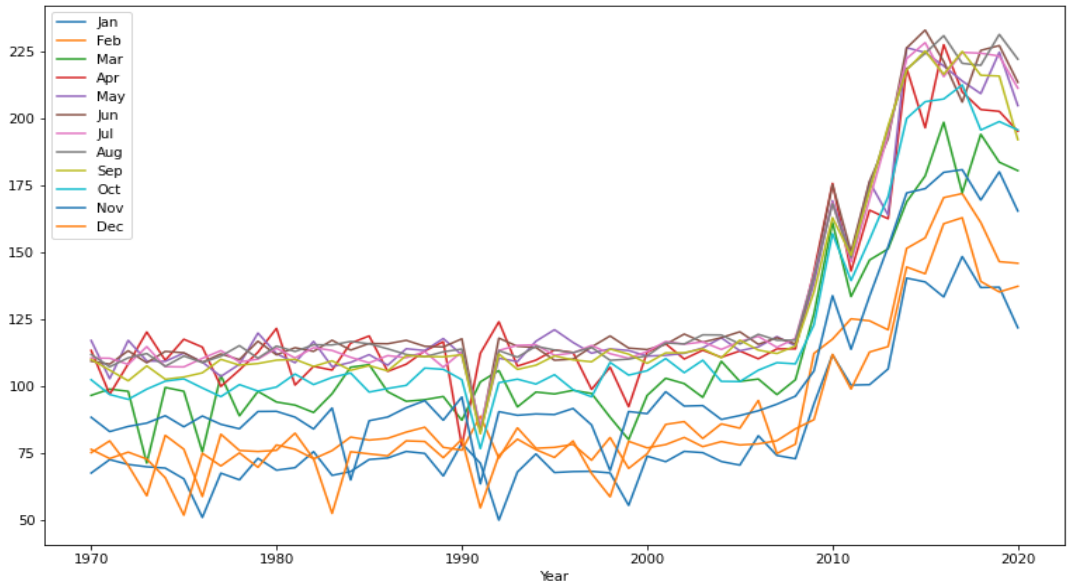


Figure 8: Sum of maximum temperature in each month of a year

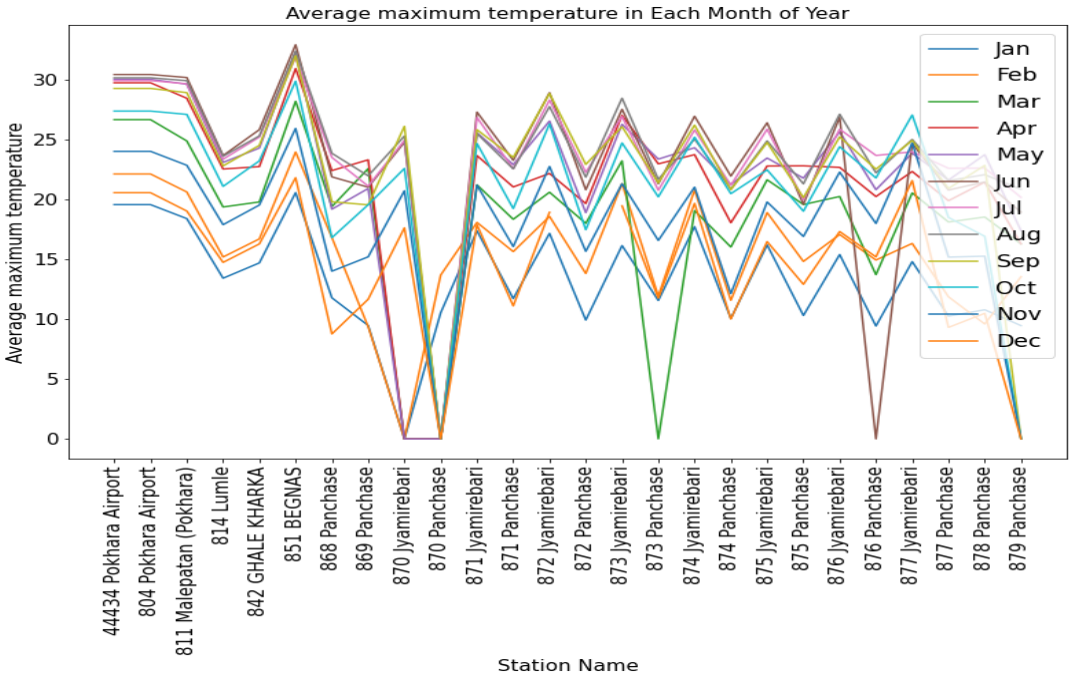


Figure 9: Station wise average maximum temperature in each month of year

Figure 9 show the relation of average of maximum temperature in each month of a year for all stations. From Figure 9 it can be obtain that for which month of a year value of maximum temperature is highest for all stations and for which month of a year value of maximum temperature is lowest for all stations.

Hence from Figure 9 it is seen that maximum value of average of maximum temperature is 23.900741427186443 that occurred in ['Aug'], minimum value of average of maximum temperature is 13.318922668085579 occurred in ['Jan'] and Mean value 19.786718068989988.

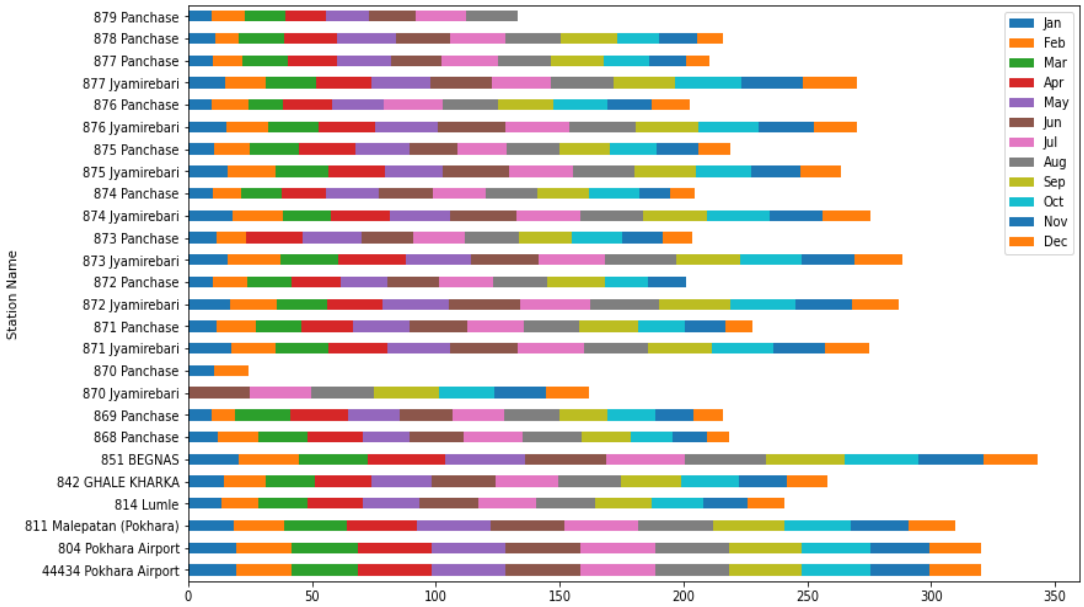


Figure 10: Bar plot of average maximum temperature in each month of year

Figure 10 is for average of maximum temperature in each month of a year for all stations. Figure 10 shows that the amount of maximum temperature is high in the months of April, May, June, July, August for all stations. Highest value is seen for 851Begnas station and 870 Panchase has data for only two months.

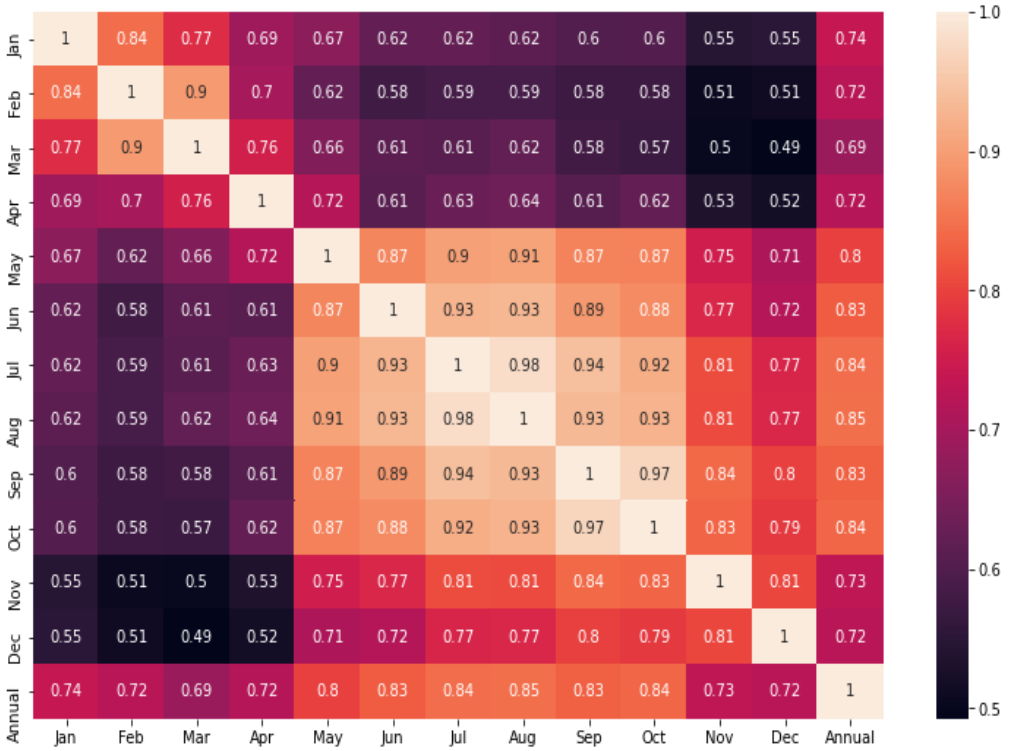


Figure 11: Maximum temperature heatmap

Figure 11 shows the co-relation (dependency) between the average maximum temperature over months. From above, it is clear that if average of maximum temperature is high in the months of Jan, Feb, March, then the value will be high annually.

3.4. Training and Testing dataset

The data set is divided into training and testing set. The training data set is used to train our model. The training set is what the model uses to learn the hidden representation of the data. The model does not get any information about the testing data. The testing data is used when the model is fully formed for evaluation of the model. The dataset is split up into a training set and testing set with 80 percent randomly chosen for training and 20 percent randomly chosen for testing for Statistical Linear Regression. 90% dataset is taken as training and 10% dataset is taken as testing dataset for Linear regression with elastic net.

3.5. Proposed Model

Two models have been proposed in this research work. One is a simple statistical linear regression model with the ability to predict feature and another is Linear regression with elasticnet and hyperparameter. Training was done by feeding the pre-process data to the model. The model trained on the data and learned the latent dependencies in the data. Each model can predict a single feature. It was hypothesized that such specialization would lead to better predictive abilities in the model.The prediction model performance is validated by deploying the models with independent verification dataset and calculating MAE, RMSE and observed vs. predicted correlation from various metrics. The MAE is the arithmetic average of the absolute values of the differences between the forecast and observation pairs and RMSE is the square root of average squared difference between the forecast and observation pairs.

The difference between the observed value of the dependent variable (y) and the predicted value ($\hat{y}$) is called the residual (e). Each data point has one residual.

Residual = Observed value - Predicted value $e = y - \hat{y}$.

In other words the distance between the regression function line and the plotted data would be termed as the residual. The Mean absolute difference serves as the residual in this case. Mean is the simplest and most widely used measure of a Mean, or average. It simply involves taking the sum of a group of numbers, then dividing that sum by the count of the numbers used in the series. Standard Deviation is a statistic that measures the dispersion of a dataset relative to its Mean. It is calculated as the square root of variance by determining each data point's deviation relative to the Mean.

The Mean absolute deviation (MAD) of a dataset is the average distance between each data point and the Mean. It gives us an idea about the variability in a dataset.

3.6. Implementation of Regression

Prediction is done using statistical regression and linear regression model. Implementation of regression algorithm involves following details.

3.6.1. Statistical Regression

The dataset is split up into a training set and testing set with 80 percent randomly chosen for training and 20 percent randomly chosen for testing. Single Linear Model uses two techniques for prediction first on whole data ignoring stations and second one on whole data including stations. It is important to evaluate how well the model fits the data and that the data meet the assumptions of the model. To evaluate the performance of algorithm the

values for MAD is calculated for training data and testing data. This model is fitted for each features of weather and both cases for whole data with and without stations are analyzed.

3.6.2. Linear Regression

With Scikit-Learn it is extremely straight forward to implement linear regression models by importing linear regression. The scikit-learn Python machine learning library provides an implementation of the Elastic Net penalized regression algorithm via the ElasticNet class. Elastic net a penalized linear regression model that includes both the L1 and L2 penalties during training. Using the terminology from "The Elements of Statistical Learning," a hyperparameter "*alpha*" is provided to assign how much weight is given to each of the L1 and L2 penalties. This allows a balance of both penalties, which can result in better performance than a model.

Linear regression with ElasticNet and fine tuning of alpha parameter to value 0.5 is used as model for this research work.

4. Results and Analysis

4.1. Statistical Regression

Single Linear Model uses two techniques for prediction first on whole data ignoring stations and second one on whole data including stations. It is important to evaluate how well the model fits the data and that the data meet the assumptions of the model. To evaluate the performance of algorithm the values for MAD is calculated for training data and testing data. This model is fitted for maximum temperature and both cases for whole data with and without stations are analyzed.

4.1.1. Single Linear Model on Whole Data Ignoring Stations

This involves prediction of maximum temperature for the current month with predictor variables as maximum temperature in previous three months. Data is arranged in 4 columns with first three columns as the predictor variables and the last column is dependent variable. For each month from April to December, four columns are appended at the bottom of the data. Training/Testing is split in the ratio 80:20 randomly

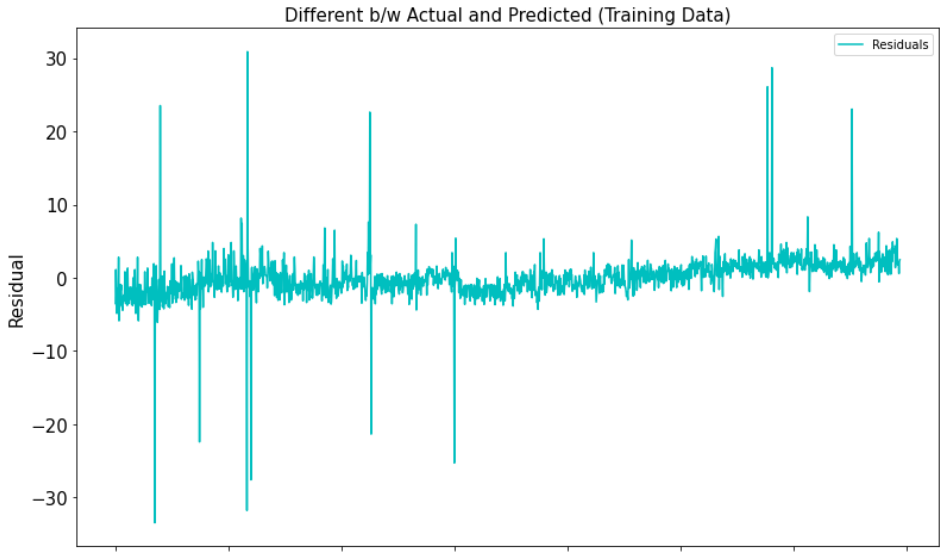


Figure 12: Maximum temperature training residual data (Whole data ignoring stations)

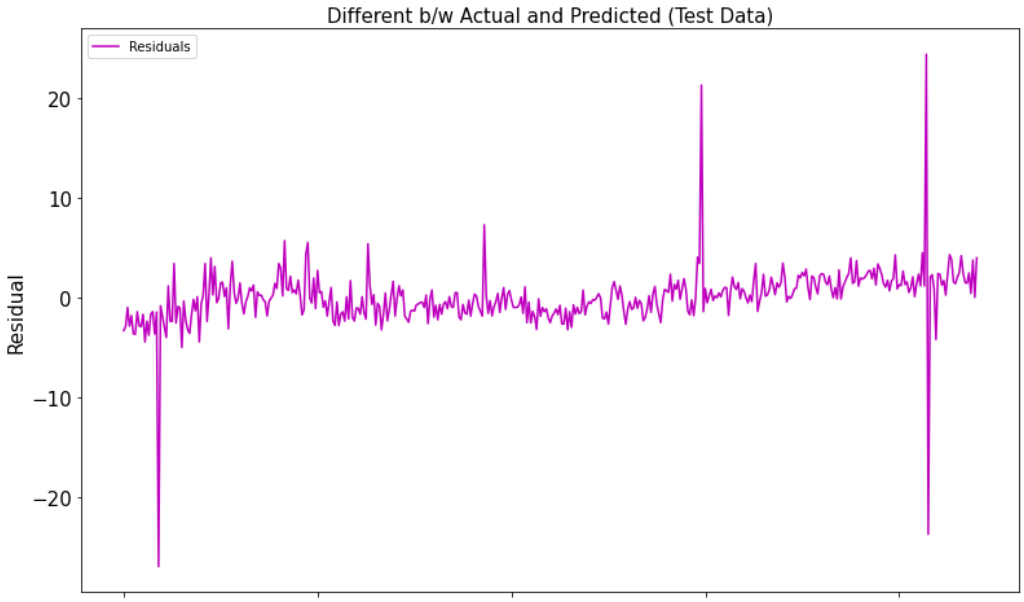


Figure 33: Maximum temperature test residual data (Whole data ignoring stations)

From Prediction of maximum temperature using this model it is observed that mean absolute deviation (MAD) for Training Data is 1.7008368209709208 and mean absolute deviation (MAD) for Test Data is 1.5599955248303865

4.1.2. Single Linear Model on Whole Data Including Stations

This involves prediction of maximum temperature for the current month with predictor variables as maximum temperature in previous three months and the stations. As stations is a categorical variable consisting of 26 values, 26 dummy binary variables are added in place of categorical variable to use in the regression.

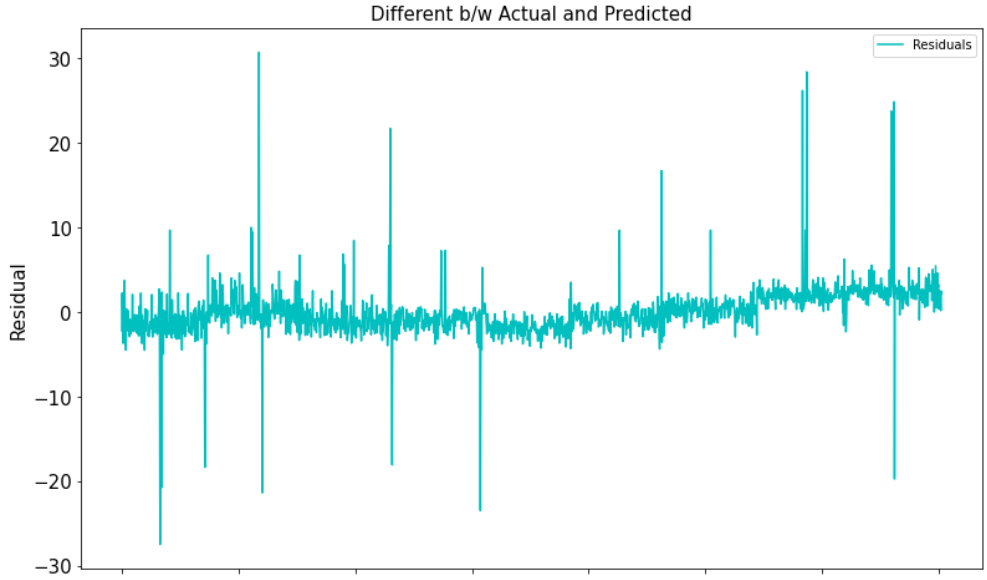


Figure 14: Maximum temperature training residual data (Whole data ignoring stations)

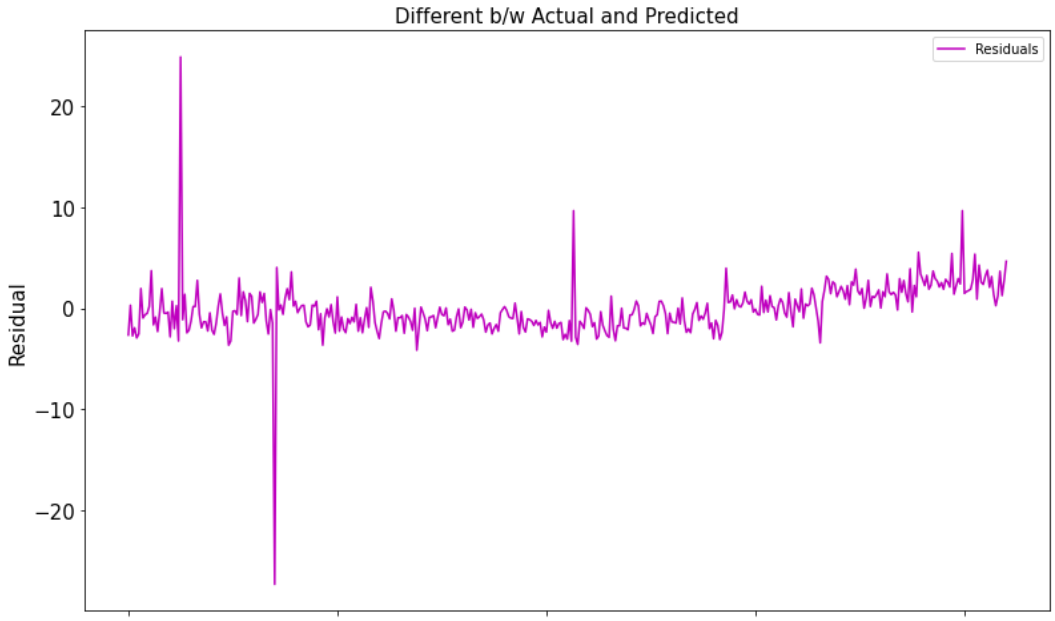


Figure 15: Maximum temperature test residual data (Whole data ignoring stations)

Data is arranged in 30 columns with 29 columns as the predictor variables and the one column is dependent variable Out of 29 variables, three are the maximum temperature for previous three months and 26 are the binary variables to be used for stations. For each month from April to December, columns are appended at the bottom of the data. Training/Testing is split in the ratio 80:20 randomly (Figure 14).

From Prediction of maximum temperature using this model it is observed that mean absolute deviation (MAD) of Training Data is 1.6636933551709678 and mean absolute deviation (MAD) of Test Data is 1.6896411530963766 (Figure 15).

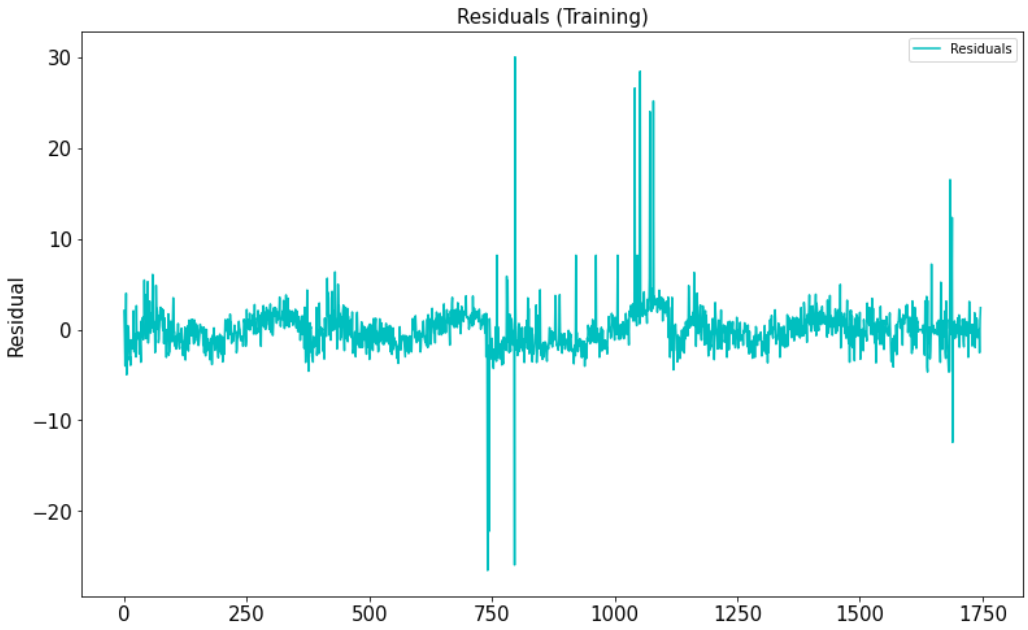


Figure 16: Maximum temperature training residual plot

4.1.3. Linear Model Fitted to Each Stations Category Independently

There will 26 different linear models for each category corresponding to each stations. First Data is extracted for each station. For each months from April to December, data is appended to end of the data. There will be four columns (one dependent variable and three independent variables). Training/Testing is split in the ratio 80:20 randomly. From Prediction of maximum temperature separately for all stations using this model, it is observed that overall MAD of Training for this model is 1.5059538276396982 and overall MAD of Testing for this model is 1.5059538276396982 (Figure 16).

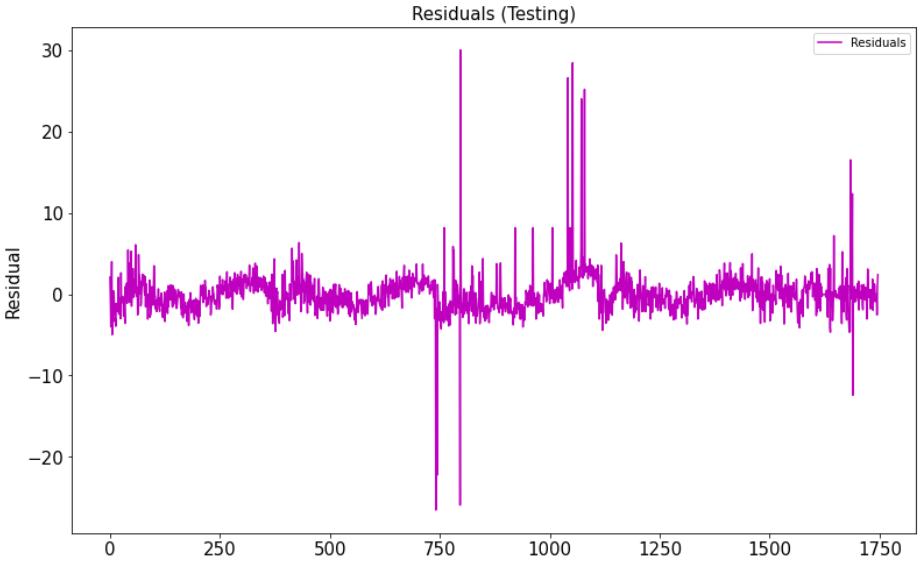


Figure 17: Maximum temperature test residual plot

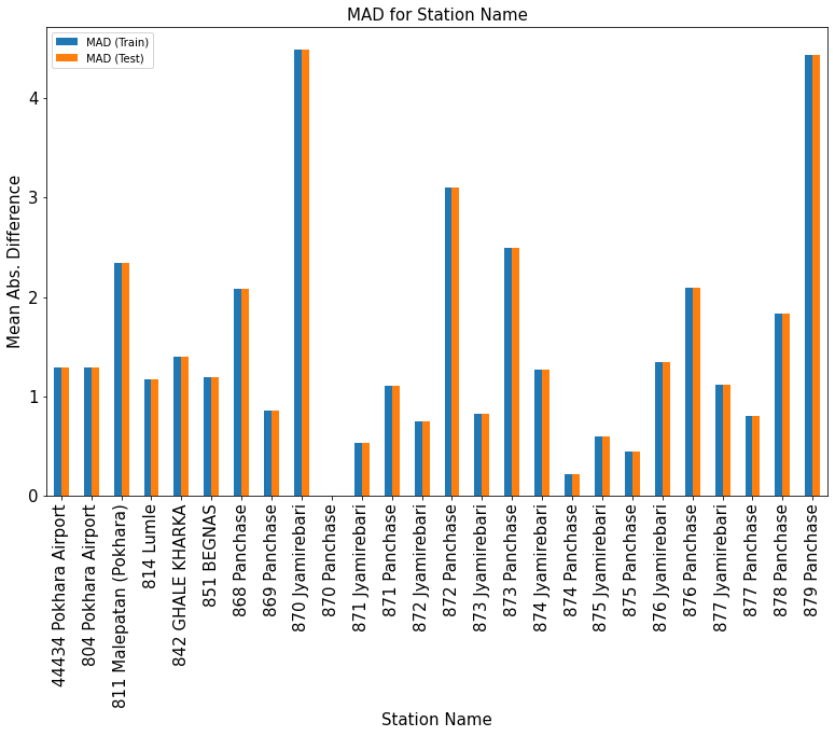


Figure 18: Maximum temperature MAD for all stations independently

From Prediction of maximum temperature separately for all stations using this model, it is observed that overall MAD of Training for this model is 1.5059538276396982 and overall MAD of Testing for this model is 1.5059538276396982 (Figure 17).

From this plot it is observed that MAD for training data and MAD for test data is almost same for all stations of maximum temperature. Maximum MAD for train and test data is seen highest in 870 Jyamirebari and 879 Panchase. Also lowest value seen in 874Panchase. 870 Panchase has zero value.

4.2. Linear Regression

For prediction the data in the last three months is used, prediction of data in the next consecutive month is calculated.

For complete dataset three months training data is (1960, 3) and three months testing data is (218, 3). From complete dataset three months used for training and testing. Ratio of training and test is 90:10 (Figure 17).

Hence output of model obtained are Mean Absolute Error: 1.78 and Root Mean squared error: 3.10

Since testing and validation is performed and analysis for an individual year 2015, 2017, 2019 is done. Following are obtained value for evaluation in terms of Mean and Standard Deviation (Figure 18).

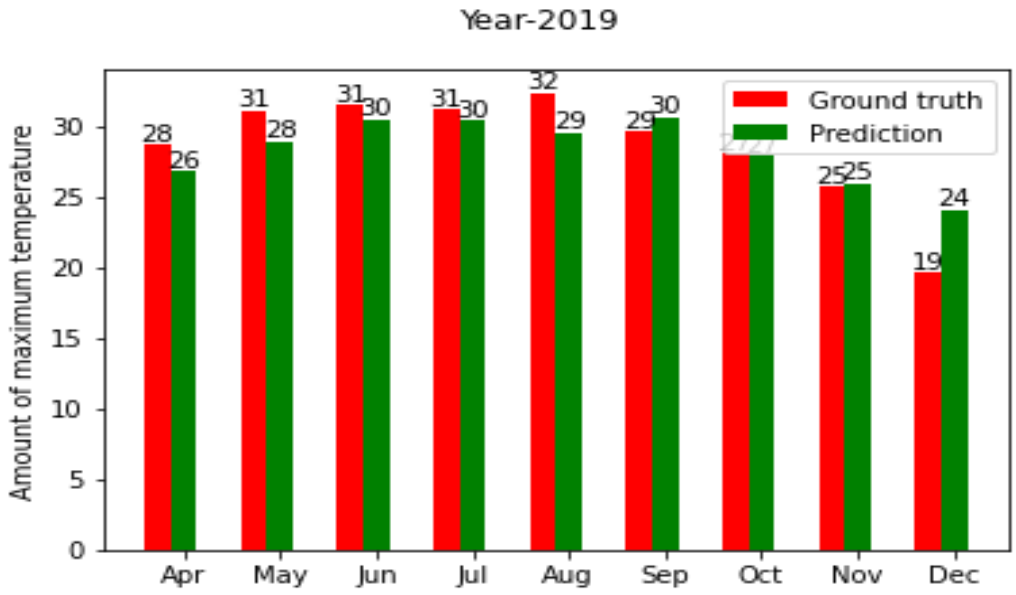


Figure 19: Maximum temperature actual and predicted data 2019(from complete dataset)

Actual value Mean of maximum temperature for 2019 is 28.626594983333334 and Predicted value Mean of maximum temperature for 2019 is 28.27502959801521. Similarly, actual value standard deviation of maximum temperature is 3.7478995707031264 and Predicted value standard deviation of maximum temperature is 2.160080524171568 (Figure 19).

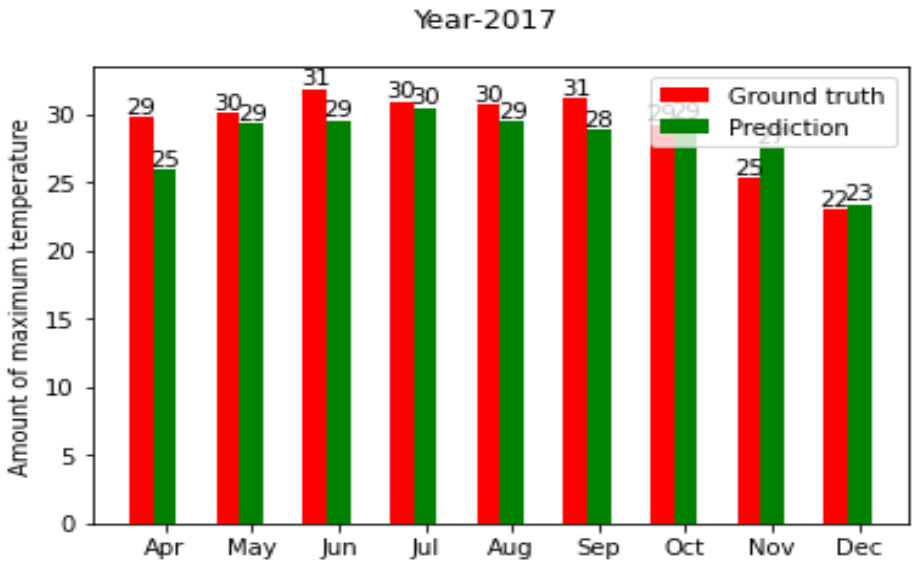


Figure 20: Maximum temperature actual and predicted data 2017(from complete dataset)

Actual value Mean of maximum temperature for 2017 is 29.09594982 and predicted value Mean for 2017 is 28.204524145648318. Similarly, actual value standard deviation of maximum temperature for 2017 is 2.801054025179093 and predicted value standard deviation for 2017 is 2.1274119698727825 (Figure 20).

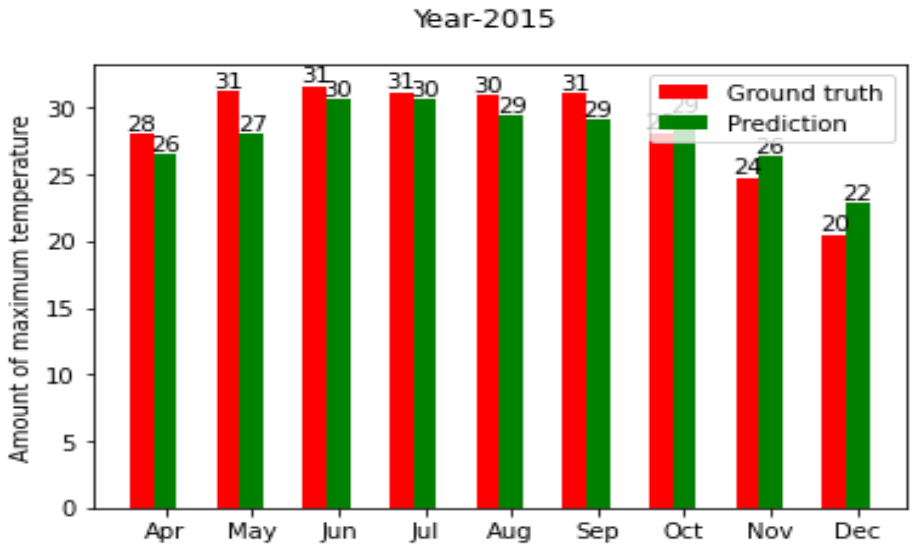


Figure 21: Maximum temperature actual and predicted data 2015(from complete dataset)

Actual value Mean of maximum temperature for 2015 is 28.60001194777778 and Predicted value Mean of maximum temperature for 2015: 28.09667842086293. Similarly, Actual value standard deviation of maximum temperature is 3.5908008863781373 and Predicted value standard deviation is 2.3787833125144324 (Figure 21).

6. Conclusion

In this research work, performance of weather prediction with simple statistical linear regression and linear regression with elastic net and hyperparameter are presented and evaluated on the dataset that is obtained from

department of hydrology and metrology. Various visualizations of data were observed which helped in implementing the approaches for prediction. Prediction of maximum temperature for the current month with predictor variables in previous three months and the stations was done using both models separately.

For a given data in previous three-month, prediction of current months is done. Training and testing using complete dataset and dataset of a station (804Pokhara airport) was done and Prediction of Particular station (804Pokhara airport) for three years (2019, 2017, 2015) were obtained. Hence, Prediction of weather feature in each month and in each year was done.

Higher correlation between observed and predicted data was analyzed using various methods like MAE, RMSE, Standard Deviation and Mean value. Performance analysis of proposed statistical linear regression model was done for linear model using whole data excluding stations, linear model using whole data including stations and linear model fitted to each station category independently. Mean Absolute Differences between actual and predicted Training and Testing data for whole data including and ignoring stations are 1.6636933551709678, 1.6896411530963766 and 1.7008368209709208, 1.5599955248303865 respectively. MAD of Training and Testing for model fitted to each station category independently are 1.5059538276396982 and 1.5059538276396982 respectively. Also machine learning approach of linear regression with elasticnet and hyperparameter was analyzed for complete dataset case and mean absolute error and root mean square error obtained were 1.78 and 3.10 simultaneously.

Hence overall Observations indicates these regression models worked well for prediction of Maximum Temperature. The analysis emphasizes that the prediction performance is good at Long term (months).

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References

[1] Denis Riordan, and Bjarne K Hansen, “A fuzzy case-based system for weather prediction.” Engineering Intelligent Systems, Vol .10, No.3. 2002

[2] Guhathakurtha, P., “Long-Range monsoon rainfall prediction of 2005 for the districts and sub-division kerala with artificial neural network.” Current Science, Vol.90, No.6, 25. 2006

[3] Jae H.Min., Young-chan Lee. “Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters.” Expert Systems with Applications, 28, pp.603-614. 2005.

[4] Mohandes, M.A., Halawani, T.O., Rehman, S and Ahmed Hussain, A. “Support vector machines for wind speed prediction.” Renewable Energy, 29, pp.939-947. 2004

[5] Pal, N.R., Srimanta Pal, Jyotirmoy Das, and Kausik Majumdar, “SOFM-MLP: A Hybrid Neural Network for Atmospheric Temperature Prediction.” IEEE Transactions on Geoscience and Remote Sensing, Vol.41, No, 12, pp.2783-2791. 2003

[6] Pao-Shan Yu., Shein-sung Chen., I-Fan Chang. “Support vector regression for real- time flood stage forecasting.” Journal of Hydrology, 328, pp. 704-716. 2006

[7] Stanislaw Osowski and Konrad Garanty, "Forecasting of daily meteorological pollution using wavelets and support vector machine." Engineering Applications of Artificial Intelligence, 20, pp.745-755. 2007

[8] Wei-Zhen Lu. Wen-Jian Wang. "Potential assessment of the support vector machine method in forecasting ambient air pollutant trends." Chemosphere, 59, pp.693-701. 2005

[9] Baklanov. Integrated Modeling for Forecasting Weather and Air Quality: A Call for Fully Coupled Approaches. Atmospheric Environment. Elsevier. 2011

[10] Maunder J., R.W. Katz and A.H. Murphy, economic value of weather and climate forecasts. Climatic Change,45(3-4), pp. 601-606, 2000.

[11] Normakristagaluh. Artificial Neural Network for Rainfall Forecasting in Statistical Downscaling. Bogor. Thesis. Institute Pertanian Bogor. 2004.

[12] WECS, "Energy sector synopsis report," 2010.

[13] J. Fan, B. Chen, L. Wu, F. Zhang, X. Lu, and Y. Xiang,"Evaluation and development of temperature-based empirical models for estimating daily global solar radiation in humid regions," *Energy*, vol. 144, pp. 903–914, 2018.

[14] M. A. Behrang, E. Assareh, A. Ghanbarzadeh, and A. R. Noghrehabadi, ")e potential of different artificial neural network (ANN) techniques in daily global solar radiation modeling based on meteorological data," *Solar Energy*, vol. 84, no. 8, pp. 1468–1480, 2010.

[15] B. Amrouche and X. le Pivert, "Artificial neural network based daily local forecasting for global solar radiation," *Applied Energy*, vol. 130, pp. 333–341, Oct. 2014.

[16] P. Oliveira, J. Soares, M. Z. Boznar, P. Mlakar, and ˇ J. F. Escobedo, "An application of Neural Network Technique to correct the dome temperature effects on Pyrgeometer measurements," *Journal of Atmospheric and Oceanic Technology*, vol. 23, no. 1, pp. 80–89, 2006.

[17] S. Belaid and A. Mellit, "Prediction of daily and Mean monthly global solar radiation using support vector machine in an arid climate," *Energy Conversion and Management*, vol. 118, pp. 105–118, 2016.

[18] R. Majhi, G. Panda, G. Sahoo, A. Panda, and A. Choubey, "Prediction of S&P 500 and DJIA stock indices using particle swarm optimization technique," in *The IEEE World Congress on Computational Intelligence on Evolutionary Computation (CEC2008)*. IEEE, 2008, pp.1276–1282.

[19] Y. Zhang and L. Wu, "Stock market prediction of S&P 500 via combination of improved bco approach and bp neural network," *Expert Syst. Appl.*, vol. 36, no. 5, pp. 8849–8854, 2009.

[20] S. T. A. Niaki and S. Hoseinzade, "Forecasting s&p500 index using artificial neural networks and design of experiments," *Journal of Industrial Engineering International*, vol. 9, no. 1, pp. 1–9, 2013.

[21] Sheta, H. Faris, and M. Alkasassbeh, "A genetic programming model for S&P 500 stock market prediction," *International Journal of Control and Automation*, vol. 6, pp. 303–314, 2013.

[22] Lucena de, A.J, Faria Peres L, Rotunno Filho O.C, Almeida França, J.R., "Estimation of the urban heat island in the Metropolitan Area of Rio de Janeiro-Brazil", In Urban Remote Sensing Event (JURSE), 2015 Joint pp: 1-4, March 2015

[23] Sharma Y, Sisodia, S, "Temperature Prediction Based on Fuzzy Time Series and MTPSO with Automatic Clustering Algorithm", In Computational and Business Intelligence (ISCBI), 2014 2nd International Symposium, pp: 101-105, December 2014

[24] Kavitha S, Varuna S, Ramya R., "A comparative analysis on linear regression and support vector regression", In Green Engineering and Technologies (IC-GET), 2016 Online International Conference pp: 1-5, 2016.

[25] Shen R, Shen J, Li Y, Wang H., "August. Predicting usefulness of Yelp reviews with localized linear regression models", In Software Engineering and Service Science (ICSESS), 2016 7th IEEE International Conference, pp: 189-192, 2016

[26] Arjun N.N, Prema V, Kumar D.K, Prashanth P, Preekshit V, Rao K.U, "Multivariate regression models for prediction of wind speed", In Data Science & Engineering (ICDSE), 2014 International Conference, pp: 171-176, August 2014