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Project Thesis

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The thesis titled **"Temperature Bias Correction using Machine Learning Algorithms"** has been submitted to the following respected members of the board of examiners of the department of computer science in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science on **December 10, 2022,** and has been accepted as satisfactory.

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Abstract

Human habitats on earth depend on many factors. There are some natural and some artificial or human factors that control the future of human habitation in the world. Human factors are not focused on in this paper. The natural factor and, more specifically, one component of it is the main center of this research. As temperature is the biggest factor in keeping the earth livable, further discussion will surround this topic. Temperature affects many other natural components like global warming, flood, and ice melting. There are direct and indirect impacts on food, agriculture, and many other things. It will be very helpful if the temperature can be predicted accurately a long time ago. Many things can be changed and saved depending on the future prediction.

The necessity of such a thing brings the idea to shape. As the prediction needs to be done based on the geographical position due to different factors and variables. This paper describes the temperature prediction focused on the data of Bangladesh. The collected data is constructed based on the historical temperature data of Bangladesh. Every station's data collection is collected for 366 days per year to provide information about minimum or maximum temperatures, humidity, barometric pressure, rainfall, and wind.

Here in this research first data was preprocessed according to the need. Established the correlations between the data. To achieve more accurate results, multiple machine learning models were performed. ANN, Ridge Regression, and Lasso Regression were the models used to perform the data feeding. The predicted results were compared between them. The most accurate result comes out of ridge regression. 86.66% for the observed max temperature and 92.38% for the observed min temperature for all stations. For single stations, accuracy is higher, and those are 98.09% for the observed max temperature and 98.63% for the observed min temperature. The method and details related to this will be found in the paper.

Keywords: Machine learning, ANN, Regression, Weather Forecasting, Numerical Weather Prediction, Climate change.

List of Figures

List of Tables

List of Abbreviations and Symbols

Abbreviations	
AI	Artificial intelligence
ANN	Artificial neural network
DT	Decision trees
RFC	Random Forest classifier
GNB	Gaussian Naive Bayes
RR	Ridge Regression
NWP	Numerical Weather Prediction

TABLE OF CONTENTS

Chapter 1

Introduction

Climate anticipation is the use of science and innovation to foresee the states of the air for a given area and time. The increasing and decreasing temperature of the planet impacts the climate, ecosystem and human development. Temperature prediction will now not solely facilitate important troubles such as floods, drought, and problems that are related to agriculture, but also it will assist in remedying for humans by way of priorly informing them about the prediction. Individuals have endeavored to anticipate the climate casually for centuries and officially since the nineteenth century. Climate conjectures are made by gathering quantitative information about the present status of the air, land, and sea and utilizing meteorology to project how the air will change at a given spot. Sometimes it is important to know the exact temperature in the future so that problems can be avoided or utilize the condition in favor of productivity. The way the world climate is changing is alarming. The necessity of preparation or finding escape from the situation only will be possible when this can be accurately predicted.[1]

So, weather prediction happens when there is a predictable distinction between real deals and the conjecture, which might be finished or under-anticipating.

The mission of the Climatology and Weather Forecasting utilizes a discussion to distribute new discoveries on Environmental standards and innovation. Right now, our essential exploration objective is to empower and help the advancement of better and quicker proportions of Environmental movement. In situations where we accept we can contribute straightforwardly, rather than through features crafted by others, we are creating our own proportions of Climatology and Weather Forecasting.[1] [2]

1.1 Background of the Study:

The historical backdrop of mathematical climate expectation thinks about how momentum climate conditions as a contribution to numerical models of the air and seas to foresee the climate and future ocean express (the course of mathematical climate forecast) have changed throughout the long term. However, in the first attempt physically during the 1920s, it was not until the approach of the PC and virtual experience that calculation time was decreased to not exactly the gauge period itself. ENIAC was utilized to make the principal figures using PC in 1950, and throughout the long term, all the more remarkable PCs have been utilized to build the size of introductory datasets just as incorporate more convoluted forms of the situations of movement. The improvement of worldwide anticipating models prompted the main environment models. The improvement of restricted region (territorial) models worked with progress in gauging the tracks of typhoons just as air quality during the 1970s and 1980s. [3]

Since the result of figure models dependent on barometrical elements requires amendments close to ground level, model result insights (MOS) were created during the 1970s and 1980s for individual estimate focuses (areas). The MOS applies factual strategies to post-process the result of dynamical models with the latest surface perceptions and the figure point's climatology. This strategy can address model goals just as model inclinations. Indeed, even with the expanding force of supercomputers, the estimated expertise of mathematical climate models just reaches out to around fourteen days into the future, since the thickness and nature of perceptions along with the turbulent idea of the incomplete differential conditions used to ascertain the figure present mistakes which twofold like clockwork. The utilization of model group figures since the 1990s assists with characterizing the gauge vulnerability and expanding climate determination farther into the future than in any case conceivable.[3]

1.2 Statement of the problem:

Current approaches to bias cannot clearly address climate change trends, and they have limited ability to mitigate. The basic premise of bias correction is that the hypothetical climate model produces competent inputs to correct bias, which includes sound representation of temperature change. Contrasting validation of lateral features is not sufficient to assess bias correction and requires further compliance and analysis. Future research should address the development of stochastic models that reduce the level and mechanisms to explicitly integrate understanding of the process.

1.3 Limitations of Study:

i. The data sample just incorporates month-to-month insights; it does exclude conjectures for day-to-day yield.

ii. Climate and environment varieties might affect how well the normal result is anticipated.

iii. A Google collab will be used to run the system covered in this study.

1.4 Goals and objective:

Two different kinds of bias correction methods can be applied to simulate daily temperature for weather forecasts. They are the Quantile Mapping (QM) and Quantile Delta Mapping (QDM). The impact of these two methods over the biases have to be investigated. Our goal is to show the effectiveness in removing the biases of both the QM and QDM methods during the validation period. QDM preserves the temperature signal well and QM artificially modifies the changed signals and changed patterns by decreasing warming and modifications. QM and QDM, these two bias correction methods can modulate the climate changing signals.[5] We will overlook the effectiveness of the temperature. We focus here on a standard sort of bias correction, particularly quantile mapping. The quantile mapping approach has the advantage of accounting for GCM biases altogether applied math moments, though, like all applied math downscaling approaches, it's assumed that biases relative to historic observations are constant throughout the projections. Whereas this quantile mapping approach has been used extensively for downscaling monthly average temperature. We have to study over these bias correction methods and research how this bias correction method can be used and intercompare modulation of the signals of the climate with the help of dataset.[5,7] As in this study, we are working on temperature, we will overlook the effectiveness of temperature prediction using different machine learning algorithms. Weather prediction based on machine learning algorithms gives better performances than other traditional statistical methods. These techniques work on different kinds of computational models based on various combinations, observations using the knowledge of different weather patterns. As a result, temperature prediction using machine learning approaches will play a significant result in terms of temperature bias correction and our goal is to explore different machine learning models to predict the temperature effectively.[7]

1.5 Significance of the study:

The results of the study will be of great benefit in the following ways-

Meteorologists use computer programs called weather models to make forecasts. Since we can't collect data from the future, models have to use estimates and assumptions to predict future weather. The atmosphere is changing all the time, so those estimates are less reliable the further you get into the future. Computer programs called weather models are used to make predictions as we cannot retrieve data from the future, models use estimates and assumptions to forecast weather. Those estimates are less reliable as the atmosphere is changing all the time.

Correcting the forecast bias of numerical weather prediction models is important for severe weather warnings. Results show that forecasts from CU-net have lower root mean square error, bias, mean absolute error, and higher correlation coefficient than those from ANO for all forecast lead times from 24 h to 240 h.

Bias correction is the process of scaling climate model outputs to account for their systematic errors, in order to improve their fitting to observations. Several bias correction methods exist. The power transformation approach can correct biases in the mean and variance.

Significance of the study of biases exists in GCM outputs when considered at a regional scale. The methods like Delta Charge, Linear Scaling, Empirical Quantile Mapping, Adjusted Quantile Mapping, Gamma-Pareto quantile Mapping were used to bias and correct the high-resolution daily maximum and minimum temperature simulation. This distinctiveness and significance of the study is to determine the analytical and optimizable forecast of the climate of a certain region. This study can also predict the intended and future forecasting climate changings. [9]

1.6 Chapter Overview:

Robust projection of temperature variability and change, particularly at regional scale, are necessary for impact studies. The advancement of computer technologies has enabled climate models to simulate more processes in detail and on a finer scale. In this study, attempts have been taken to improve the performance of one such GCM simulated temperature data. The GCM simulation is improved by using six bias correction methods. The performance evaluation of each bias correction technique was done in order to find the best performing methods for all the gathered data and study area.[9]

Chapter 2

Literature review

2.1 Climate Vs Weather

Climate refers to the long term, average weather forecast for a given location. The atmospheric conditions at a certain location at a specific moment are referred to as weather. The calculation of climate uses weather data stretching back more than 30 years. Contrariwise, weather is determined by calculating the regular meteorological data. Climate is very much effective for the long term planning of a country's development. In addition, weather has a significant impact on people's daily activities. Moreover, it is responsible for determining climate.

2.2 Forecast Vs Prediction

The forecast is an estimated method of predicting the outcome utilizing information from earlier datasets, occasions, and experiences. On the other hand, prediction means an idea that an event may or may not occur in the near future. Because the forecast returns a calculated result, we get an actual reading for the future. As a result of prediction, on the other hand, we are given an estimate as to what will happen in the future. The forecast is a mathematical assertion. However, a prediction is a potential declaration. Given that it comes after an estimation result, a forecast may create business demand. Although there may or may not be a business demand for prediction, there is a significant experimental demand. We use different Machine Learning algorithms for determining the forecast. On the contrary, To calculate the level of prediction, we apply statistical analysis. The forecast is the end outcome of research. Prediction, however, is based on personal concern. The forecasting mistake can be examined. But prediction cannot use error analysis. [12]

2.3 Numerical Weather Prediction

The term "numerical prediction" refers to foretelling the value using numbers. For a particular object, this numerical possibility is determined. It makes a lot of potential events possible. Based on existing historical data, the forecast materializes or a choice is made. In numerical prediction, accuracy, resilience, interpretability, etc., are top priorities. A regression algorithm can be used to perform numerical prediction from the viewpoint of machine learning. Basically, this method seeks to forecast a value by outlining a link between known and desired factors. Decision trees, linear regression, logistic regression, etc., are some of the most popular regression techniques. The practice of NWP (Numerical Weather Prediction) is based on historical information about the ocean and atmosphere. In this procedure, parameterization is crucial. The NWP uses a series of equations to convey how various weather parameters wander. In order to predict the weather, these fundamental equations are modified in computer language. Temperature is predicted using a variety of predictor models. In order to forecast the weather, numerical models study the existing weather conditions.[13]

2.4 Neurons

Neurons are the part of the brain that helps constitute meaning. It is one of the most essential organs of the human body, responsible for receiving external input from the world outside the body. It is responsible for signal processing in our body. The sensitivity that we feel in this physical phenomenon makes it happen to us. Through the cooperation of certain cells or parts of the brain, this process develops. It contains the distinctive category mentioned below. Soma is the part containing the nucleus. Axon looks like a tail. Many axons are connected through a fatty material termed myelin. It is responsible for all expectations of an appropriate action. Dendrite takes the necessary inputs. Neurons may contain a collection of dendrites called dendritic trees. The synapse is the organ that allows communication in all the internal organs of the neuron. [14]

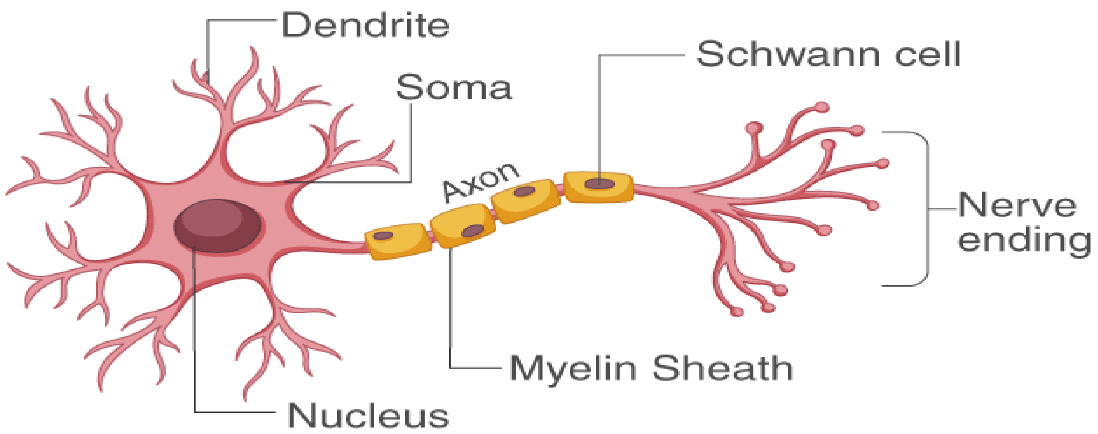


Figure 1: Neuron Scheme [14]

2.5 Artificial Neural Network

An artificial neural network (ANN) is a network consisting of artificial or invisible neurons that simulates how the human brain works. The concept of ANN is energized by neurons in the human brain. It is basically a predictive or cognitive model based on a previously defined activation function. ANN uses an algorithm that can learn and adjust itself. This network learns from existing information provided in the dataset. The signals go from the first layer to the last layer of all layers of the neural network. These classes work to get the job done. An ANN can have any number of classes and any number of entries can belong to a class. The ANN makes a conclusion after estimating the common value. ANN is structured in two main stages called forward propagation and backpropagation. The forward-propagation phase incorporates adding bias in the input, multiplying

the weights, applying an activation function, and then passing the input to the next layer. The primary purpose of the activation function is to allow the data to be informed of non-linearity. Helps identify basic types in data. The task of the backpropagation phase is to find the optimal solution. To do this, optimization functions are needed. The main motivation of the optimization function is to find the best fit for the parameters. ANN can be used for regression and classification in both cases. This is considered one of the biggest advantages of ANN. The amount of error of the ANN is detected by comparing the targeted output and the actual output. Phenomena using ANNs include spam detection, business intelligence, chatbots, and more. ANN outperforms pristine machine learning models as data volume grows. [15]

2.5.1 Structure of ANN

ANN models simulate the electrical activity of the brain and nervous system. Processors (also called neurons or perceptrons) are connected to other processing elements. Typically, neurons are arranged in a layer or vector, with the output of one layer acting as the input to the next and possibly other layers. A neuron can be connected to all or a subset of neurons in the next layer, these connections simulate the synaptic connections of the brain. The weighted data signals entering the neuron simulate the electrical excitation of the neuron and thus the transmission of information in the network or brain. The input values for a processing element, in, are multiplied by the connection weight, wn,m, simulating the enhancement of neural pathways in the brain. The learning is simulated in the ANN through adjusting the connecting forces or the weights.[15]

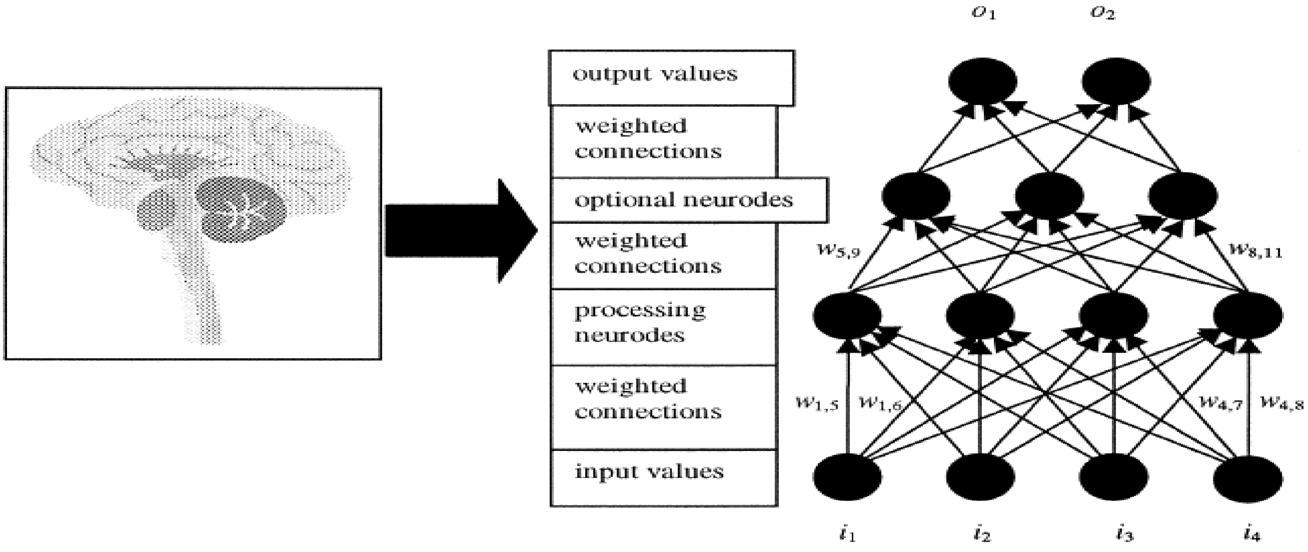


Figure 2: Structure of ANN [15]

2.5.2 Feedforward neural network

Feedforward neural network (FNN) has a multilayer perceptron and a single layer perceptron. This is the first invention in ANN and also the simplest invention. In a feedforward ANN, the input step is one-way. In these types of ANNs, there is no kind of ring between the connections of the nodes. Mostly, this type of ANN is specially used in the tasks of pattern recognition, classification, etc.[15]

2.5.3 Recurrent neural network

In Recurrent Neural Network (RNN), the input's stroll is multidirectional. It takes an input, then moves forward and also provides feedback, that is, moves in the opposite direction to provide that feedback. Most of the time, this kind of neural net is used to solve a temporary solution. As such image captioning, translation of languages etc. [16]

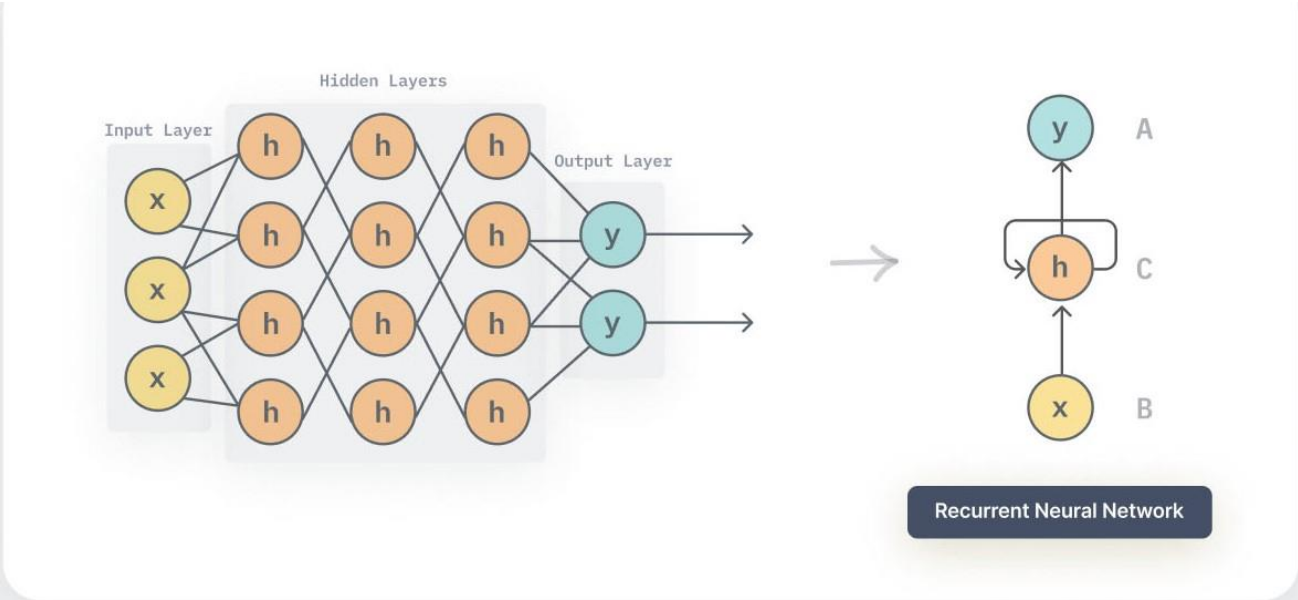


Figure 3: Structure of Recurrent Neural Network [16]

2.6 Regression

In statistical analysis, regression is used to distinguish the affiliations between factors occurring in some data. It can show both the magnitude of such an association and also determine its statistical importance. Regression could be a powerful tool for statistical induction and has moreover been used to try to predict future results based on past observations.[16]

2.6.1 Lasso Regression

In statistics and machine learning, lasso (least absolute shrinkage and selection operator; also Lasso or LASSO) is a regression analysis method that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the resulting statistical model. Lasso was originally formulated for linear regression models. This simple case reveals a substantial amount about the estimator. These include its relationship to ridge regression and best subset selection and the connections between lasso coefficient estimates and so-called soft thresholding.[16]

- Performs L1 regularization, i.e. adds penalty equivalent to **absolute value of the magnitude** of coefficients
- Minimization objective = LS Obj + α * (sum of absolute value of coefficients)

2.6.2 Ridge Regression:

Ridge regression is a way to create comprehensive models when the number of anticipating variables in a set exceeds the number of observations or when the data set shows multicollinearity (the correlation between the predictors).

- Performs L2 regularization, i.e. adds penalty equivalent to **square of the magnitude** of coefficients
- Minimization objective = LS Obj + α * (sum of square of coefficients)

While Ridge and Lasso appear to be functioning towards a common goal, the inherent properties and substantial use cases differ significantly. They work by adjusting the magnitude of the characteristic coefficients during minimizing the error between the predicted and actual observations. This is called the "regularization" technique. The main difference is how they assign penalties to the coefficients.[16]

Chapter 3

Methodology

Temperature bias correction for both maximum temperature and minimum temperature is feasible by simulating the temperature individually. In order to create a model for temperature bias correction and to describe the process properly, there has to define some random variables. Then the whole process has also fit into some prediction algorithms. The study that follows will address the data analysis methods that were developed using 38 years of climate data from various stations from 1981 to 2019. The data used for this study's temperature predictions were gathered from more than 30 stations spread out over the county, according to an assessment of 38 years' worth of data.

3.1 Data Collection

In this study, information is required to anticipate the objective of temperature bias correction. The raw data was acquired from various area meteorological stations. The entire dataset was retrieved from the website of the Bangladesh Meteorological department. There are many types of data from various stations and for various time periods available on the website.

There are eight features in the dataset, which include station id, days, maximum temperature, minimum temperature, humidity, observed wind, observed pressure, and categorical rainfall. Every day, the meteorological station has recorded the values of all-weather variables for all weather stations.

As a result, the information was tabulated within the CSV file. In the row of tablelands there are 12 months and days of the month sorted according to climate variables. A 38-year period of uncooked data (1981-2019) from the station has been used for the study.

3.2 Data Processing

The meteorology office has gathered data for a total of 38 years (1981–2019). As the statistics were raw, they had missing values and incorrectly encoded values; therefore, the missing values of the target variable were eliminated, and the other features were filled using the data's mean. The data preprocessing procedure encompassed record conversion, the management of missing values, specialized encoding, and the separation of the dataset into training and testing datasets. In the climate station, the raw data were additionally organized on a 12-monthly basis, with attributes in rows and points in columns that need to be combined and rearranged. Thus, statistics were converted from Excel format to CSV format. The utilized dataset is encrypted and structured for the model. The fundamental aspects of temperature prediction have been identified, and the 70:30 split of the testing dataset was treated as a model input. The information includes the most important temperature factors. Consideration is given to Station ID, Days, Maximum temperature, Minimum temperature, Humidity, observed wind, Observed Pressure, and Rainfall Categorical. Input for the processing of the output as a forecast of temperature will be analyzed and examined in this research.

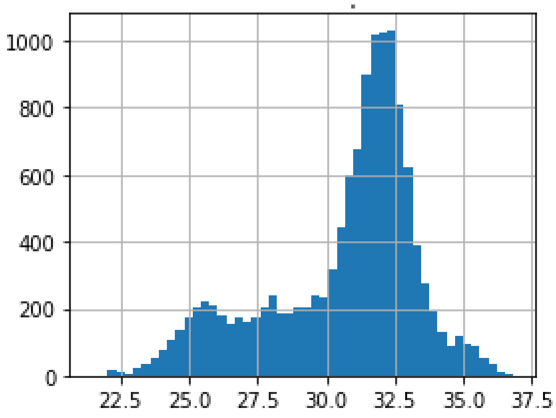


Figure 4: observedTempMax

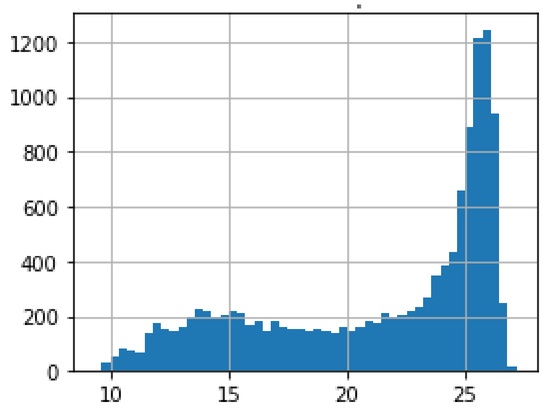


Figure 5: observedTempMin

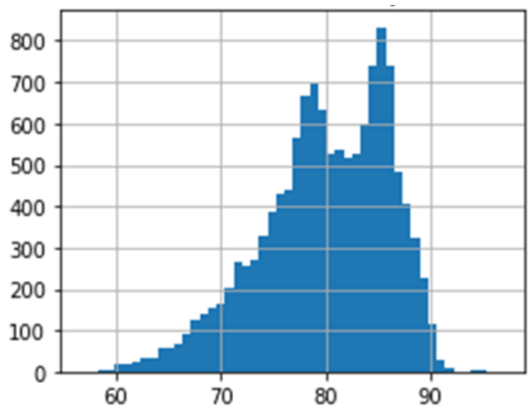


Figure 6: observedHumidity

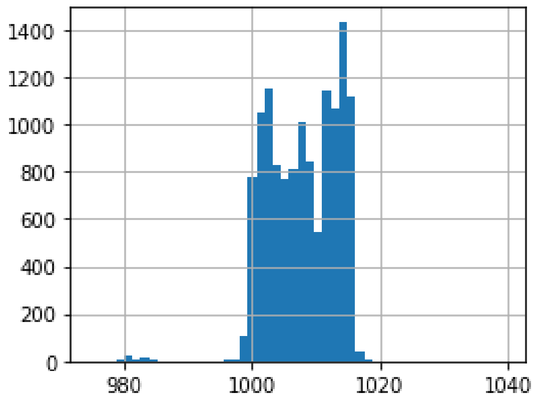


Figure 7: observedPressure

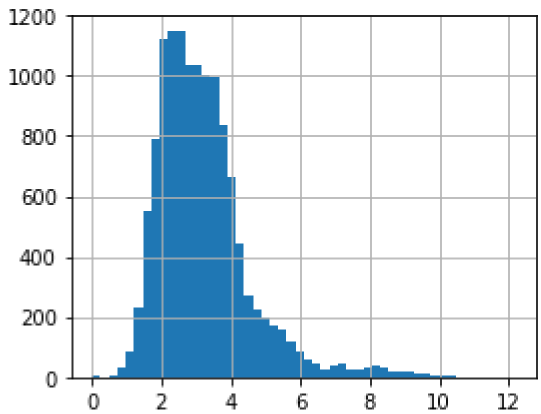


Figure 8: observedWind

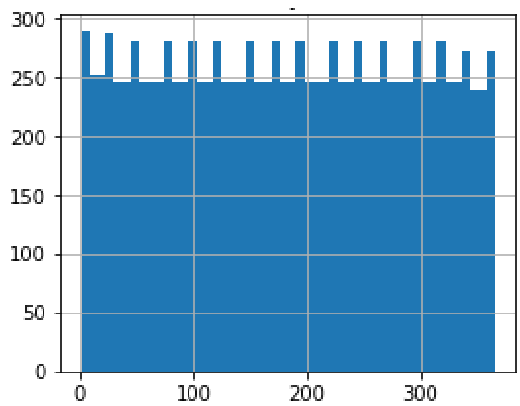


Figure 9: days

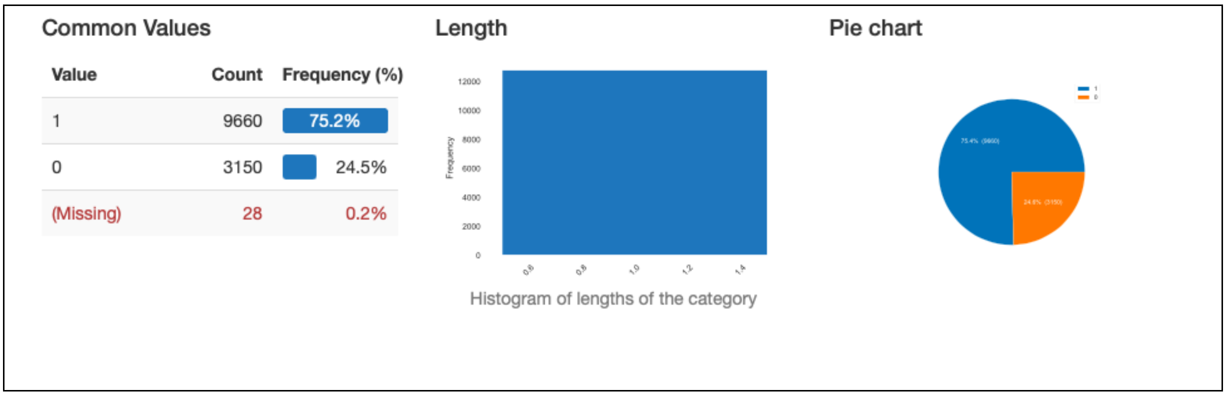


Figure 10: observed Rainfall categorical

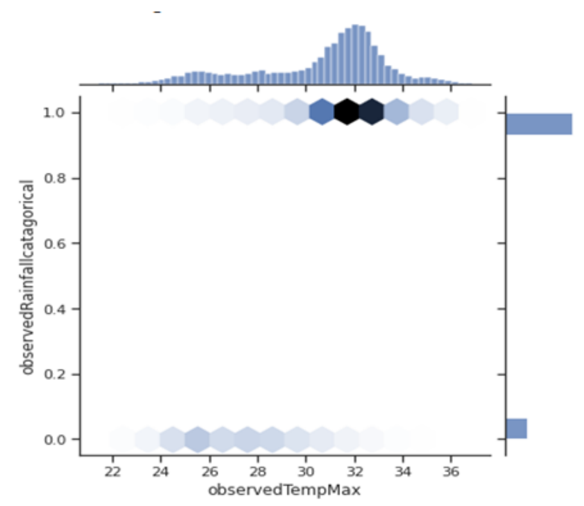


Figure 11: Interactions by observed Rainfall categorical(For max temp)

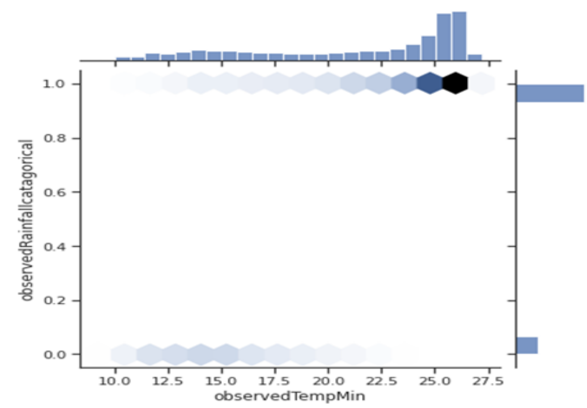
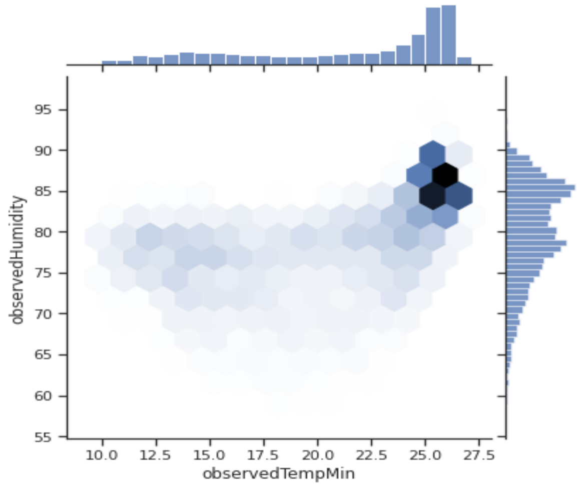


Figure 12: Interactions by observed Rainfall categorical(For min temp)



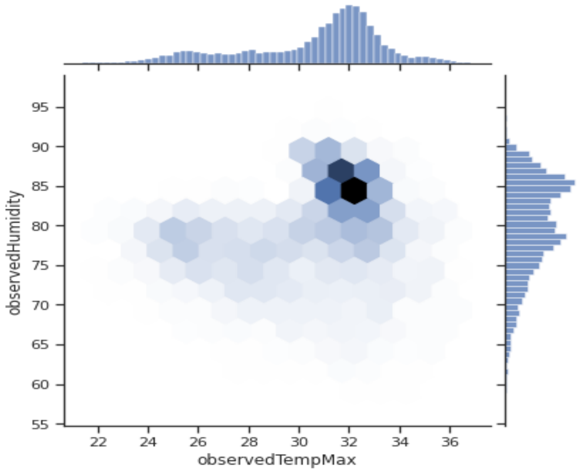


Figure 13: Interactions by observedHumidity (For min temp)

Figure 14: Interactions by observedHumidity(For max temp)

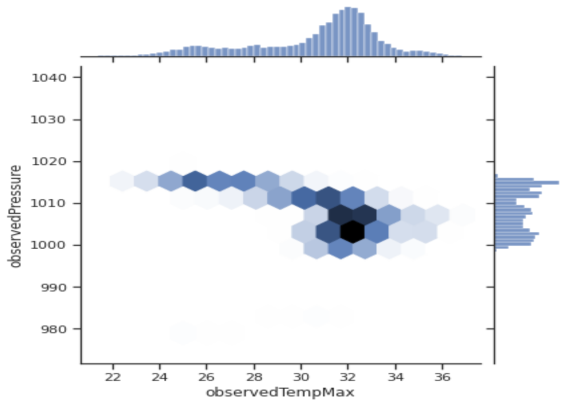


Figure 15: Interactions by observedPressure (For max temp

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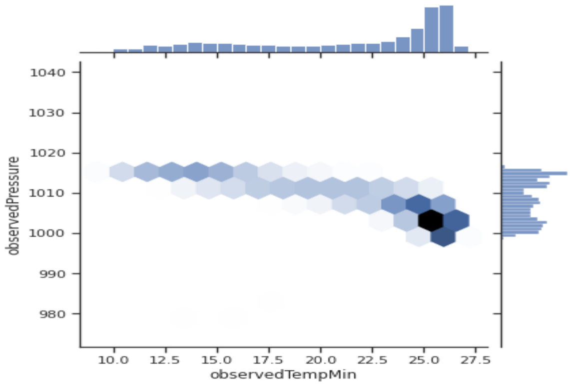
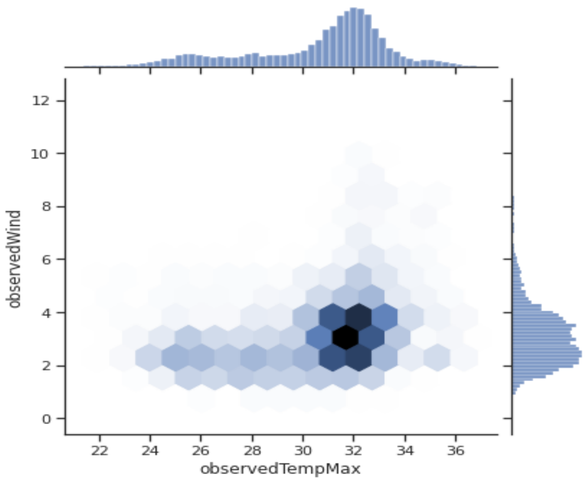


Figure 16: Interactions by observedPressure (For min temp)



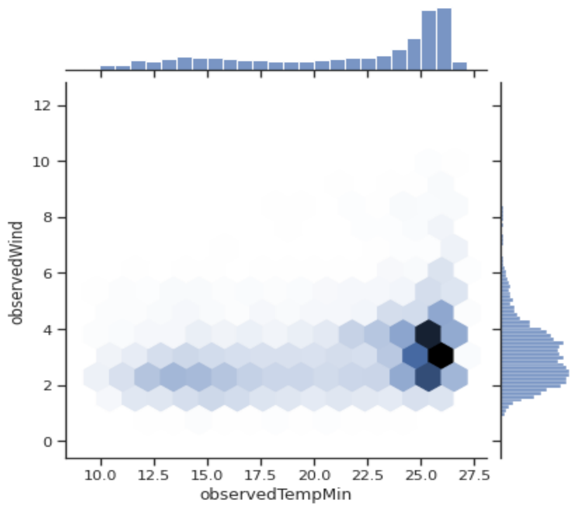


Figure 17: Interactions by observedWind (For max temp) *Figure 18: Interactions by observedWind (For min temp)*

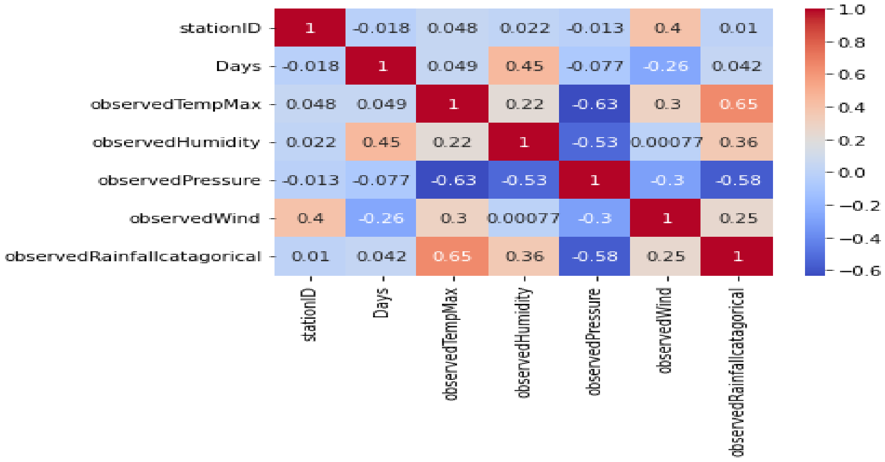


Figure 19: Correlations

3.3 Methods

We analyzed some journals where the maximum and minimum temperature prediction was used using the methods of artificial intelligence, machine learning and neural network. Artificial intelligence and neural networks involve some algorithms. For this reason, it is more difficult than artificial intelligence. [7]

In this study, the data collected from the different weather stations of different states.

3.4 Tools and Libraries Used

3.4.1 Keras

Python's significant level learning Programming interface, Keras, permits clients to execute and compute brain organizations of any intricacy without any problem. Keras is an open-source programming stage that gives counterfeit brain networks a TensorFlow point of interaction. Keras is a connection point for the TensorFlow library, so it very well might be utilized related to it Only TensorFlow 2.4 gives usefulness to profound brain organizations. Immediately access profound brain networks while as yet profiting from its ease of use, seclusion, and development potential. Preceding form 2.3, Keras was viable with various backends, including

TensorFlow, Microsoft's CNTK, Theano, mxnet, and plaidML. Keras is an undeniable level Programming interface of TensorFlow, and it gives an unlimited, decidedly powerful point of interaction for handling AI hardships with an accentuation on current profound learning. Whatever is required is given by it. It covers the simple thoughts and structure essential for making and sending ML frameworks rapidly. Keras doesn't do low-even out activities like convolution and tensor items.[10]

3.4.2 TensorFlow

AI models and complex mathematical issues can be settled with TensorFlow, a low-level programming library made by Google. There's nothing more open-source or free than TensorFlow with regards to AI programming. It very well might be applied to various applications with an emphasis on profound brain network preparation and deduction. The center pieces of TensorFlow, an emblematic number related system utilized by Google for both exploration and creation, are information stream and differential programming.

3.4.3 Scikit- Learn

The best and solid library for PCs learning Python is Scikit-realize, which is a vital part. By utilizing a Python consistency interface, it spreads out the requirement for efficient instruments for PC examination and factual demonstrating, including characterization, relapse, bunching, and dimensionality decrease. This library was made utilizing NumPy, SciPy, and Matplotlib and is principally written in Python. The library additionally makes it conceivable to do information handling activities including ascription, normalization, and normalizing. The exhibition of the model may regularly be incredibly upgraded by finishing these exercises. Furthermore, there are likewise various bundles accessible in Scikit-learn for making direct models, tree-based models, grouping models, and numerous different models.[10]

3. 5 Workflows

Right away, we gathered the dataset from the branch of meteorology Bangladesh. Then we handled the information through information cleaning and doing bunch by in panda information outline. Then in the information segment stage, we parceled the dataset in train, test, and split. Then, at that point, we committed highlight extraction and significant component determination. A short time later, we executed Choice trees (Irregular - woodland classifier), Gaussian Innocent Bayes, Fake brain organizations, Straight Relapse, Calculated Relapse, and Edge Relapse. Through these models we anticipated precipitation. Our model was adequately scholarly to characterize and distinguish the example of precipitation. The genuine outcome and forecast results were exceptionally close on account of practically the models as a whole. The precision was adequately exact. Then, at that point, we got for mistakes. We determined mean square blunder, standard deviation mistake, and cross-approval mistake. The blunder rate was high for direct relapse and furrowed relapse models and the remainder of the model's mistake was small.[11]

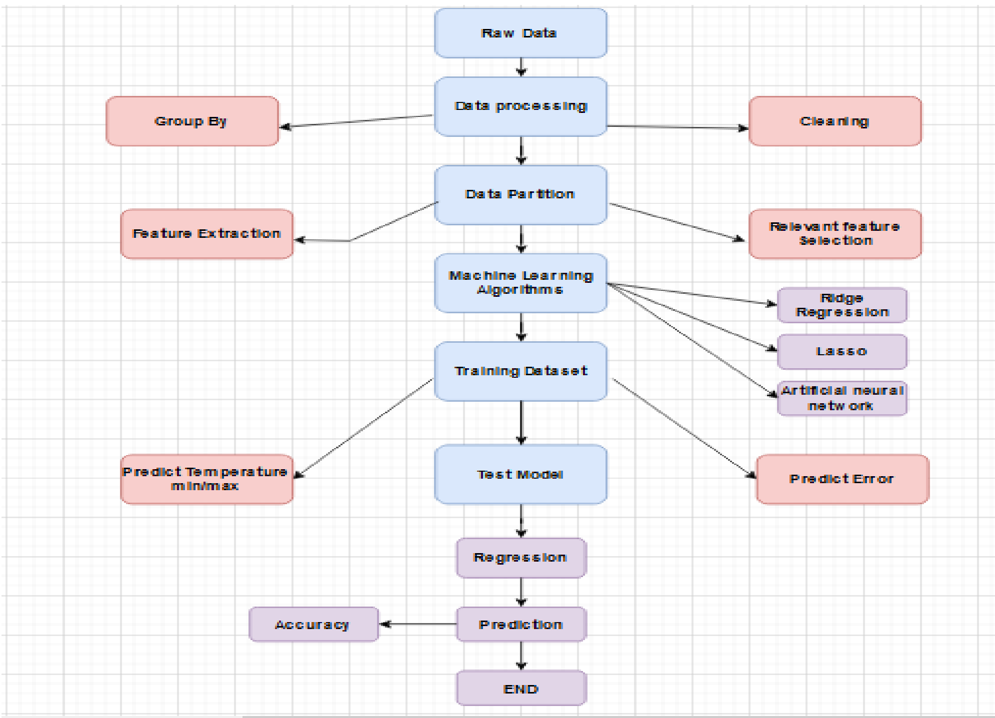


Figure 20: workflows

Chapter 4

Result And Analysis

In this study, as we have to predict temperature for temperature bias correction, we use uncooked data from the local meteorological office. As they are raw data, there must be some preprocessing and cleaning of the data set for applying various machine learning algorithms. Then various machine learning algorithms applied for the temperature prediction model to find out the best possible algorithms suitable for the best possible outcomes with better accuracy. Basically, here we have to explore the machine learning models for temperature prediction to find out which models are producing better accuracy using our dataset and to make some comparisons for the analysis of our study. In this way the following test data set generates predictions for the result in this study.

4.1 Data Correlations

A correlation between two variables exists when there is movement between them indicating a relationship. To perceive any form of data relationship, it is essential to comprehend correlations. In the graph below, we can see that the column of interest is 'observed temperature minimum' and 'observed temperature maximum'. The column 'observed Pressure' has a negative correlation (-0.785690) with minimum temperature. It also has a negative correlation (-0.633993) with maximum temperature. Therefore, we proceed without the observed pressure column to get a better outcome.

	stationID	Days	observedTempMax	observedTempMin	observedHumidity	observedPressure	observedWind	observedRainfallcatagorical
stationID	1.000000	-0.008462	0.042371	-0.000458	0.021993	-0.012309	0.395726	0.009716
Days	-0.008462	1.000000	0.045088	0.205650	0.449015	-0.076285	-0.264310	0.041882
observedTempMax	0.042371	0.045088	1.000000	0.866812	0.218090	-0.633993	0.297390	0.650359
observedTempMin	-0.000458	0.205650	0.866812	1.000000	0.569985	-0.785158	0.284572	0.713382
observedHumidity	0.021993	0.449015	0.218090	0.569985	1.000000	-0.530233	0.000775	0.360916
observedPressure	-0.012309	-0.076285	-0.633993	-0.785158	-0.530233	1.000000	-0.298153	-0.575454
observedWind	0.395726	-0.264310	0.297390	0.284572	0.000775	-0.298153	1.000000	0.247986
observedRainfallcatagorical	0.009716	0.041882	0.650359	0.713382	0.360916	-0.575454	0.247986	1.000000

Figure 21: Correlations of Weather parameters in full data set.

4.2 Analysis and comparison of results

Our objective was to identify the optimal model that increases specificity while keeping an acceptable level of sensitivity utilizing machine learning prediction methods and techniques. For data modeling training, we utilized a variety of methodologies and distinct volumes of data. Initially, we collect unprocessed data sets from the local weather department. The following stage was to preprocess the data using various ways. Every station's data collection is collected for 366 days per year to provide information about minimum or maximum temperatures, humidity, barometric pressure, rainfall and wind. Our objective is therefore to observe the intended minimum temperature and maximum temperature for our specified meteorological parameters. As part of the data set preparation process, we utilized various methods of normalizing or scaling. The following tables provide further information about the results.

- A full data set has been taken into consideration for machine learning models

	For ObservedMaxTemp	**For ObservedMinTemp**
Artificial neural network	Test Accuracy: 0.9911430478096008	Test Accuracy: 0.9031956195831299
Lasso Regression	Lasso regression r2 score: 0.8439750258043328 Error (MSE): 1.1896072243250688	Lasso regression r2 score(Accuracy): 0.9130673592655392 Error (MSE): 2.1010998051383956

	For ObservedMaxTemp	For ObservedMinTemp
Ridge Regression	Ridge regression r2 score: 0.8666603909492627 Error (MSE): 1.0166434125892791	Ridge regression r2 score: 0.9238670002436189 Error (MSE): 1.8400802000407088

Table 1: Comparison results of Observed maximum and minimum temperature

From the above table, we can see that there are two columns. The first one is for the observed maximum temperature and the second one is based on the observed minimum temperature. Both columns have been taken from the whole dataset. For the observed maximum temperature, we have taken the observedTempMax as the target column and the rest of the dataset is trained for the model. The accuracy score obtained by applying ANN (Artificial Nural Network) is 0.9911430478096008 for observed maximum temperature and this value is higher than the other two machine learning algorithms. The accuracy score for lasso regression is 0.8439750258043328 and Ridge regression is 0.8666603909492627. On the other hand, for the observed minimum temperature, the algorithm that gives the highest accuracy is Ridge regression which is 0.9238670002436189. The artificial neural network's accuracy score is 0.9031956195831299 which is slightly lower than the lasso regression (accuracy score: 0.9130673592655392). The error rate is slightly higher than the observed maximum temperature for Ridge regression and Lasso regression. But for the artificial neural network, the error rate has been decreased for observed minimum temperature.

- Assuming one station has all day data, and another has data for all the stations.

	When selected data for all station		**When considering only single Station for data set**	
	For ObservedMaxTemp	**For ObservedMinTemp**	**For ObservedMaxTemp**	**For ObservedMinTemp**

Artificial neural network	Test Accuracy: 0.9911430478096008	Test Accuracy: 0.9031956195831299	Test Accuracy: 0.2529153525829315	Test Accuracy: 0.8628803491592407
Lasso Regression	Lasso regression r2 score: 0.8439750258043328 Error (MSE): 1.1896072243250688	Lasso regression r2 score: 0.9130673592655392 Error (MSE): 2.1010998051383956	Lasso regression r2 score: 0.9692228926785726 Error (MSE): 0.3509382486657159	Lasso regression r2 score: 0.9711131733975075 Error (MSE): 0.9159183714652578
Ridge Regression	Ridge regression r2 score: 0.8666603909492627 Error (MSE): 1.0166434125892791	Ridge regression r2 score: 0.9238670002436189 Error (MSE): 1.8400802000407088	Ridge regression r2 score: 0.9809200217576205 Error (MSE): 0.21756086688169246	Ridge regression r2 score: 0.9863840186785504 Error (MSE): 0.43172369223718843

Table 2: Comparison of results data table

From the above table, we can see that there are four columns. But we are differentiating the columns mainly in two parts. The main difference between the two columns is based on the size of the data collection. For the left side column, we have taken the whole dataset for all the weather stations and in the right-side column, we have taken the dataset for a single station. We accomplished the best accuracy for the whole data set, when we trained it using machine learning models of the artificial neural network (accuracy score: 0.9911430478096008) for maximum observed temperature. It is comparatively higher accuracy for maximum temperature using the whole dataset of about 38 years. But the accuracy score drops a bit when we used other machine learning algorithms like Ridge regression and lasso regression. For the ridge regression, the accuracy score is (accuracy_score: 0.8666603909492627). The accuracy score for lasso regression is (accuracy_score: 0.8439750258043328), which is a little lesser than ridge regression for maximum observed temperature. For the minimum observed temperature, the accuracy for the artificial neural network, ridge regression and lasso regression are very close. The accuracy for ridge regression is (accuracy_score: 0.9238670002436189), it is higher than the other two machine learning algorithms. The accuracy score for the lasso regression is (acccuracy_score: 0.9130673592655392), slightly lower accuracy but an ideal score. Although the accuracy of the artificial neural network is a little bit less accurate (accuracy_score: 0.9031956195831299) for the observed minimum temperature.

The machine learning models significantly outperformed than before when we trained them with less data from only one station rather than the entire data set. When we used the whole data set, the accuracy of ridge regression for maximum temperature was almost 87%, for lasso regression it was 84%. On the other hand, when we used just a single station data, we got an accuracy score of 98% for ridge regression and 97% for lasso regression. Which is much higher accuracy than before. But when we used the artificial neural network model, the accuracy decreased to 83% for maximum temperature. Although we got lower accuracy for the fewer data of only one station for an artificial neural network for minimum temperature also. On this occasion, the accuracy drops almost 4%. The surprising fact is that when we used a single station data, the error rate of ridge regression (0.217) and lasso regression (0.350) drops significantly when we consider for maximum observed temperature. It happens in a same way for observed minimum temperature also. In this case the error rate of ridge regression is (0. 431) and for lasso regression it is (0. 915).
So, if we sum up the entire analysis of the result, we can acquire the following comprehensive rating for our study and data set.

- **Ridge Regression > Lasso Regression > ANN (Artificial Neural Network)**

4.3 Best Machine learning algorithm model for our data set

As part of our paper research and implementation, we used multiple machine learning algorithms with diverse methodologies to create a better prediction model and achieve better outcomes. We had to explore various machine learning algorithms to find out which algorithms are giving better accuracies for temperature prediction for both maximum and minimum temperature. In our study we applied Artificial Neural Network model, Ridge Regression model and Lasso Regression model for the prediction of maximum and minimum temperature. We discovered that ridge regression and lasso regression provide the highest level of test accuracy with less error-proneness for our dataset among all methods and methodologies. All machine learning algorithms performed well and accurately in our experiments. Regardless, we discovered that the machine learning algorithms discussed below provide the best information for our datasets and study.

4.3.1 Ridge Regression

Ridge regression is a method of estimating the coefficients of multiple-regression models in scenarios where the independent variables are highly correlated. According to this study, our data set would be best suited to Ridge regression. In Ridge, Regression outcomes are continuous values. So, there would be many possible answers for this such as any numeric value. In this study, the accuracy score for ridge regression is: 0.980 and mean squared error: is 0.217 for observed maximum temperature. On the other hand, for observed minimum temperature, the accuracy score for ridge regression is: 0.986 and mean squared error: is 0.431. As we can see that in this study, the ridge regression model gave much more accuracy and very less error-prone than others. The ridge regression models predict much more accurately than other models with little data training.

```
[ ] from sklearn.linear_model import *
    from sklearn.metrics import r2_score

[ ] rid = Ridge()

[ ] h=rid.fit(x_train,y_train)
    y_pred = rid.predict(x_test)

[ ] r2_score(y_test, y_pred)

    0.8666603909492627

[ ] from sklearn.metrics import mean_squared_error

    mse = mean_squared_error(y_test, y_pred)
    mse

    1.0166434125892791
```

Figure 22: Ridge max temp (All station)

```
[ ] from sklearn.linear_model import *
    from sklearn.metrics import r2_score

[ ] rid = Ridge()

[ ] h=rid.fit(x_train,y_train)
    y_pred = rid.predict(x_test)

[ ] r2_score(y_test, y_pred)

    0.9238670002436189

[ ] from sklearn.metrics import mean_squared_error

    mse = mean_squared_error(y_test, y_pred)
    mse

    1.8400802000407088
```

Figure 23: Ridge min temp (All station)

```
[ ] from sklearn.linear_model import *
    from sklearn.metrics import r2_score

[ ] rid = Ridge()

[ ] h=rid.fit(x_train,y_train)
    y_pred = rid.predict(x_test)

[ ] r2_score(y_test, y_pred)

    0.9809200217576205

[ ] from sklearn.metrics import mean_squared_error

    mse = mean_squared_error(y_test, y_pred)
    mse

    0.21756086688169246
```

Figure 24: Ridge max temp (Single Station)

```
[ ] from sklearn.linear_model import *
    from sklearn.metrics import r2_score

[ ] rid = Ridge()

[ ] h=rid.fit(x_train,y_train)
    y_pred = rid.predict(x_test)

[ ] r2_score(y_test, y_pred)

    0.9863840186785504

[ ] from sklearn.metrics import mean_squared_error

    mse = mean_squared_error(y_test, y_pred)
    mse

    0.43172369223718843
```

Figure 25: Ridge min temp (Single Station)

4.3.2 Lasso Regression

This study suggests that Lasso regression, which comes after Ridge Regression, would be the most appropriate for our data set. Our projected results in Lasso Regression are continuous numbers. Therefore, there are numerous potential responses to this question, including any integer value. In this investigation, the mean squared error for the measured maximum temperature is 0.350, and the accuracy score for lasso regression is 0.969. The accuracy score for lasso regression is 0.971 for the observed minimum temperature, whereas the mean squared error is 0.915. As we can see, the lasso regression model performed significantly better in this investigation than ANN in terms of accuracy and error-proneness. The lasso regression models make better accurate predictions with less training data.

```
[ ] from sklearn.linear_model import *
    from sklearn.metrics import r2_score

[ ] las = Lasso()

[ ] h=las.fit(x_train,y_train)
    y_pred = las.predict(x_test)

[ ] r2_score(y_test, y_pred)

    0.8439750258043328

[ ] from sklearn.metrics import mean_squared_error

    mse = mean_squared_error(y_test, y_pred)
    mse

    1.1896072243250688
```

Figure 26: Lasso Max Temp (All station)

```
[ ] from sklearn.linear_model import *
    from sklearn.metrics import r2_score

[ ] las = Lasso()

[ ] h=las.fit(x_train,y_train)
    y_pred = las.predict(x_test)

[ ] r2_score(y_test, y_pred)

    0.9130673592655392

[ ] from sklearn.metrics import mean_squared_error

    mse = mean_squared_error(y_test, y_pred)
    mse

    2.1010998051383956
```

Figure 27: Lasso Min temp (All station)

```
[ ] from sklearn.linear_model import *
    from sklearn.metrics import r2_score

[ ] las = Lasso()

[ ] h=las.fit(x_train,y_train)
    y_pred = las.predict(x_test)

[ ] r2_score(y_test, y_pred)

    0.9692228926785726
```

Figure 28: Lasso max temp (Single Station)

```
[ ] from sklearn.linear_model import *
    from sklearn.metrics import r2_score

[ ] las = Lasso()

[ ] h=las.fit(x_train,y_train)
    y_pred = las.predict(x_test)

[ ] r2_score(y_test, y_pred)

    0.9711131733975075
```

Figure 29: Lasso min temp (Single Station)

4.3.3 Artificial Neural Network

According to this study, Artificial Nural Network (ANN) comes after Lasso Regression is the least suitable for our dataset. For maximum temperature as a target, we got test accuracy equal to 0.9911430478096008 and test accuracy equal to 0.9031956195831299 for minimum temperature. To train the dataset we used one input layer, three hidden layers and one output layer. We also set epochs=100, batch size=64 and validation split = 0.2. As our number of data was twelve thousand plus, a batch size larger than 64 affected accuracy. The number of columns in the features list was 5 so we set the input dimension as five and separated the entire dataset into an 80:20 ratio for training and testing.

```
early_stopping = callbacks.EarlyStopping(
   min_delta=0.001, # minimium amount of change to count as an improvement
   patience=20, # how many epochs to wait before stopping
   restore_best_weights=True,
)
# Initialising the NN
model = Sequential()
# layers
model.add(Dense(units = 128, kernel_initializer = 'normal', activation = 'relu', input_dim = 5))
model.add(Dense(units = 256, kernel_initializer = 'normal', activation = 'relu'))
model.add(Dense(units = 256, kernel_initializer = 'normal', activation = 'relu'))
model.add(Dropout(0.25))
model.add(Dense(units = 256, kernel_initializer = 'normal', activation = 'relu'))
model.add(Dropout(0.5))
model.add(Dense(units = 1, kernel_initializer = 'normal', activation = 'linear'))

model.compile(loss='mean_absolute_error', optimizer='adam', metrics=['mean_absolute_error'])
model.summary()

checkpoint_name = 'Weights-{epoch:03d}--{val_loss:.5f}.hdf5'
checkpoint = ModelCheckpoint(checkpoint_name, monitor='val_loss', verbose = 1, save_best_only = True, mode ='auto')
callbacks_list = [checkpoint]
history=model.fit(x_train, y_train, epochs=100, batch_size=64, validation_split = 0.2, callbacks=callbacks_list)
```

Figure 30: ANN (All Station)

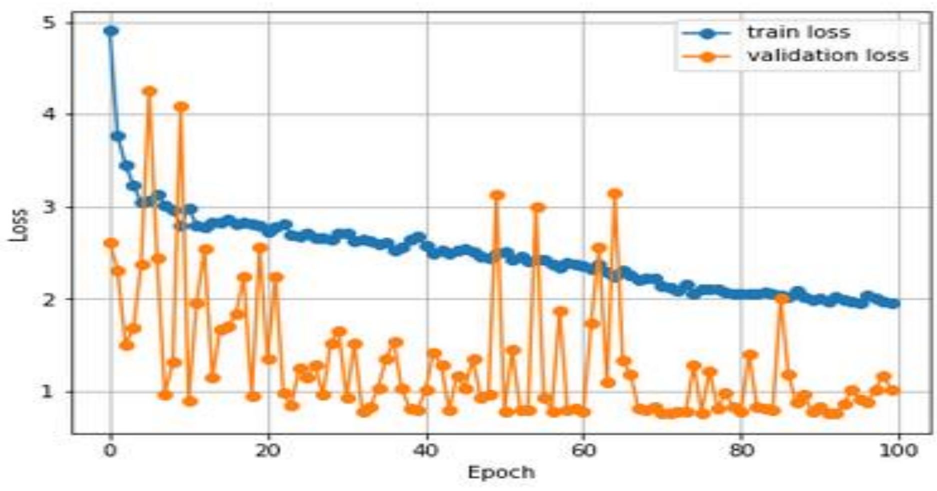


Figure 31: ANN model training for max temperature as a target (All Station)

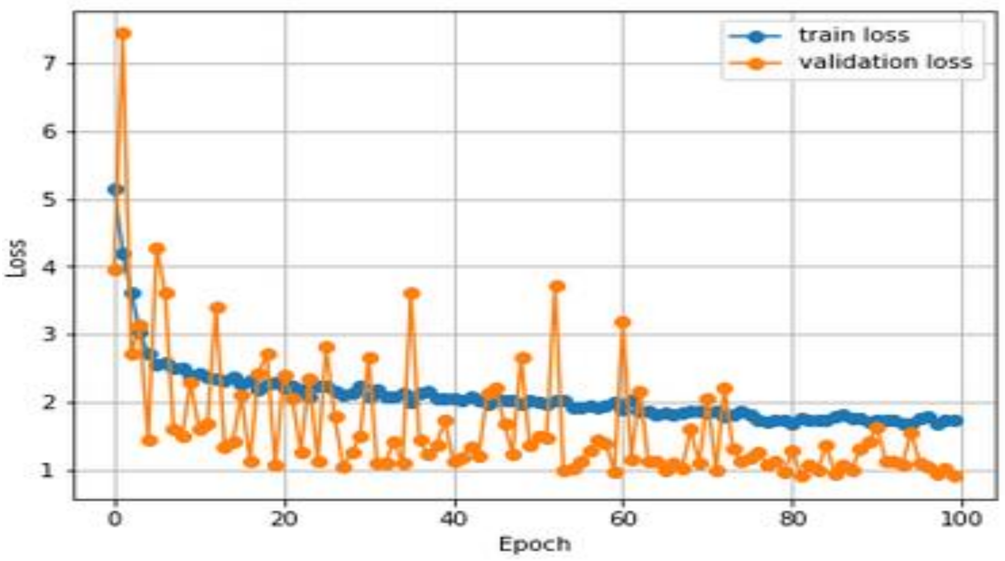


Figure 32: ANN model training for min temperature as a target (All Station)

Chapter 5

Discussion & Conclusion

5.1 Significance of Result:

The natural qualities utilized in this examination, which were gotten from a meteorological station and estimated by estimating gadgets, were analyzed for their pertinence with the impacts of temperature. The relevance of the natural attributes was resolved in light of the analysis' Pearson connection values, which are shown in Tables 1 and 2 for the day-to-day temperature expectation for both extreme and least temperature. This study inspected temperature expectation utilizing ecological qualities with a relationship coefficient bigger than 0.2. Essentially, it utilizes a level of relationship between each action to distinguish the five critical ecological elements: temperature (minimum/most extreme), relative moistness, tension, wind,

and precipitable water. As per the reviewer's examination relationship, there is a strong negative relationship among observedPressure' and relative mugginess of about - 0.5.
To execute the investigation, we need to gather the entire arrangement of information which comprises a year's noticed temperature, relative dampness, strain, wind and precipitation in light of various stations. To prepare and assess the three AI models ANN, LR (Lasso Relapse) and RR (Edge Relapse) for the expectation of day to day greatest and least temperature, this review utilized the appropriate climate factors.
In this review, we decided the precision for tether relapse for most extreme temperature is 0.843 and for least temperature it expanded to 0.913, which is for the entire dataset. In any case, utilizing a solitary station informational index the precision improves definitely. We got the greatest temperature exactness is 0.969 and least temperature precision is 0.971. The exactness score of Edge relapse for greatest temperature is 0.981 and for least temperature, it is further developed a smidgen which is 0.986. The exactness of the counterfeit brain network gives better precision around 0.991 for greatest temperature and for least temperature it is 0.903. However, fake brain networks gave a lot of lower precision for a lesser dataset when we considered a solitary station as it were.

5.2 Limitations:

There are several constraints on our ability to collect and handle data, as well as to train machine learning algorithms, which have led to mixed levels of precision. One issue we ran into was that the data collection we used contained too many missing values. Using the fill function and the value above, we've populated all the missing values. As a result, our precision and error rate will suffer. We ran into certain restrictions while gathering the dataset. And this affected how machine learning algorithms were taught. There's even a column that has a negative link with the ones we want to keep. When dealing with a single station, there was a severe lack of data with which to train the machine-learning algorithms. If there were additional data, we could train our models more effectively.
A preprocessing step was performed on the dataset, which revealed the presence of duplicate rows. This resulted in the elimination of those rows. The data had to be entered into the database, retrieved, and a new data sheet based on the group data had to be created as part of the preprocessing. Data for feature extraction has only been lightly evaluated, making comparison difficult. We didn't go to the extremes of hyper-tuning or perfect tuning the algorithm used in the creation of the artificial neural network. That means there would have to

be restrictions. For this reason, it would appear that Training accuracy is subpar. When we trained it with our regression algorithms for others and Algorithms, we did not pick all of the options linked to better training. Perfect normalization is needed for better training of artificial neural networks and logistic regression; however, we did some fundamental normalizations.

5.3 Future work:

We will be able to accurately anticipate lowest or maximum temperature in the future using our machine learning algorithms based on this research. It is also feasible to forecast future temperatures. If we set every option, we can configure our algorithms so they can be trained more effectively. If we use all the best normalization approaches to our data, our training accuracy will improve. Our artificial neural network models are highly and flawlessly adjustable. Using the appropriate loss function and other methods, we can produce hidden layers and final layers. We can experiment with various test datasets to see whether our machine learning algorithms can reliably anticipate how much data will fluctuate. We can also insert other weather variables in our data collection that are not already there. We can preprocess our data using a method that is almost perfect. We can extract features from data and perform a variety of data analytics. To achieve significantly better results, we will carry out further study and create a variety of machine learning algorithms. To predict rain and winter, as well as different tragedies, we may use a variety of climate or weather study techniques. so that our population will be shielded from storms, heat waves, droughts, floods, and other natural disasters.

5.4 Conclusion

Temperature is one of the essential weather parameters in the current world for many reasons, as global warming is increasing at an alarming rate worldwide. In Bangladesh, it is much more critical to parameters as we have been facing massive climate change in recent years. In Bangladesh, the lands throughout the country produce different types of crops all over the country every year. And this production is dependent on temperature also, as many studies and research are going on based on agriculture. It is also essential in sectors like metrology. In this study, the data set was collected from different meteorological stations throughout the country based on time series from 1981 to 2019. As we worked on weather parameters of different stations throughout the country, it helped sketch the weather variations. In this study, we used some machine learning algorithms and analyzed them to predict minimum and maximum temperature based on the correlation of different weather parameters. We used the Ridge regression algorithm, Lasso regression algorithm and Artificial Neural Network (ANN) algorithm to analyze this study. We achieved the best accuracy for temperature prediction using the Ridge regression algorithm. We found good accuracy using lasso regression also. However, our study was good enough to find the purpose of this study, but there is more to come. There are many aspects to improve this prediction model further using more hybrid algorithms in future.

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APPENDICES

APPENDIX A

Dataset of Observed Weather

station ID	Days	observedTemp Max	observedTemp Min	observedHumidit y	observedPress ure	observedWind	observedRainf allcatagorical
10120	1	23.18205128	10.73589744	77.5862069	1016.255172	3.968965517	0
10120	2	22.9974359	10.73846154	78.65517241	1016.424138	4.017241379	0
10120	3	22.27692308	10.56666667	80.55172414	1016.227586	4.306896552	0
10120	4	22.11538462	10.71282051	79.86206897	1016.027586	4.234482759	1
10120	5	22.32564103	10.27435897	79.75862069	1015.627586	4.434482759	0
10120	6	22.64871795	10.02820513	79	1015.765517	3.410344828	0
10120	7	22.51282051	10.31025641	79.65517241	1016.141379	3.972413793	0
10120	8	22.53333333	10.18205128	78.93103448	1015.827586	3.806896552	1
10120	9	22.09230769	10.49487179	80.03448276	1015.786207	3.679310345	1
10120	10	21.91794872	9.892307692	79.4137931	1015.903448	3.55862069	0
10120	11	22.10512821	10.01025641	80.24137931	1015.724138	4.117241379	0
10120	12	22.03076923	10.04358974	79.5862069	1015.431034	3.765517241	0
10120	13	22.32307692	9.679487179	78.82758621	1015.065517	3.993103448	1
10120	14	22.24102564	9.556410256	79.86206897	1015.210345	4.175862069	0
10120	15	22.43846154	9.679487179	79.65517241	1015.665517	3.655172414	0
10120	16	22.93589744	9.994871795	78.17241379	1015.306897	3.8	1
10120	17	22.83076923	10.26153846	77.96551724	1015.486207	3.803448276	1
10120	18	23.11282051	9.976923077	77.27586207	1015.496552	3.693103448	0
10120	19	23.00769231	10.11794872	77.93103448	1015.051724	4.744827586	0
10120	20	22.3538461	10.54615384	80.0344827	1015.2620689	4.18620689	1