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Data-Driven Meteorological Forecasting For Divisional Cities In Bangladesh: An ANN- Based Climate Study

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ABSTRACT

Bangladesh is highly susceptible to the impacts of climate change. In Bangladesh, variations in temperature, rainfall, relative humidity (RH), wind speed, cloud coverage and sunshine duration can strongly influence agriculture, public health, and socio-economic conditions. Accurate city-level climate predictions are essential for informed planning. Yet most existing research focuses on national-level trends often overlooking local variability. This study aims to bridge that gap by forecasting climate parameters for eight divisional cities of Bangladesh for the period 2023–2042. Two machine learning techniques Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) were applied to predict maximum temperature, rainfall and relative humidity with model performance assessed via MAE, MSE, RMSE, and R^2. ANN emerged as the most reliable model for these predictions.

The results reveal distinct spatial patterns. Cities including Khulna, Dhaka, Rajshahi, Rangpur, and Chittagong show an increase in maximum temperatures and reductions in rainfall and relative humidity. Conversely, Sylhet and Barishal exhibit declining temperatures while rainfall and humidity rise. On the other hand, Mymensingh demonstrates simultaneous increases in all three parameters. These findings underscore that climate change effects are heterogeneous across Bangladesh. Understanding these patterns is crucial for developing effective regional adaptation strategies. Areas experiencing rising temperatures and reduced rainfall may face heightened heat stress and water scarcity. Whereas wetter regions may encounter increased flooding and humidity related challenges. This research provides city specific data-driven insights that can assist policymakers, researchers and planners in designing targeted interventions to mitigate climate risks.

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1. Introduction

Bangladesh is one of the most climate vulnerable countries in the world due to its geographical location, socio-economic exposure, and dependence on climate sensitive sectors such as agriculture and public health [1]. Accurate localized climate predictions are critical to support informed planning, disaster preparedness and efficient resource management. Variations in temperature, rainfall, humidity, wind speed, cloud coverage, and sunshine duration can significantly impact crop yields, water resources and public health outcomes. While global and national level climate studies provide important insights. They often overlook city-specific trends that are crucial for regional decision making and policy formulation [2]. Recent advances in machine learning have enabled more precise weather forecasting by capturing complex and nonlinear

relationships among meteorological variables. Techniques such as Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) are particularly effective in modeling temporal patterns and predicting future climate parameters based on historical records [3]. ANN excels at identifying intricate nonlinear dependencies among multiple features, whereas RNN is highly suitable for sequential and time-series data due to its memory retention capability. By leveraging these models, policymakers, agricultural planners, and other stakeholders can obtain more reliable and actionable climate forecasts to inform adaptation strategies. In this study, we have focused on eight divisional cities of Bangladesh- Dhaka, Khulna, Rajshahi, Rangpur, Chittagong, Sylhet, Barishal, and Mymensingh covering historical meteorological data from 1949 to 2022. Seven key features are considered: maximum temperature, minimum temperature, rainfall, relative humidity, wind speed, cloud coverage, and bright sunshine. Correlation analysis is performed to understand interdependencies among these features. The predictive performance of ANN and RNN is evaluated using standard metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2. The findings reveal distinct regional variations such as increasing temperatures with decreasing rainfall and humidity in some cities and contrasting patterns in others highlighting the heterogeneous nature of climate change impacts across Bangladesh.
Understanding these spatially differentiated trends is vital for developing adaptive strategies to mitigate heat stress, water scarcity, and flooding risks. This research provides a city level data-driven foundation to support evidence-based decision-making in climate-sensitive sectors including agriculture, public health, and infrastructure planning.

2. Literature Review

Recent studies have demonstrated the growing importance of machine learning (ML) techniques for accurate climate and weather forecasting in regions with high climate variability such as Bangladesh. Machine learning models particularly Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) have been successfully employed to predict key meteorological parameters including temperature, rainfall and humidity showing superior performance over traditional statistical methods [4]. Hossain and Amin [5] highlighted the significant impacts of climate change on Bangladesh's agriculture emphasizing that shifts in temperature and erratic rainfall patterns reduce crop yields and exacerbate vulnerability to pests and diseases. Integrating ML techniques into agricultural forecasting has proven effective in improving predictive accuracy, enabling policymakers and farmers to make informed decisions for resource management and crop planning [6]. For instance, Islam et al. [7] demonstrated that ML models such as Random Forest and ANN could reliably predict Aman rice yields under varying climatic conditions. Furthermore, hybrid modeling approaches, combining models like CNN and XGBoost have shown enhanced performance in rainfall prediction leveraging the strengths of multiple models to improve forecast reliability in localized regions [8]. Despite these advancements, challenges remain including limited availability of high-quality local data, model interpretability and the need for region-specific adaptations. Addressing these issues is critical to develop robust, actionable climate predictions that can support proactive planning in agriculture, water management and disaster preparedness across Bangladesh.
In our study, both Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) models have been used. Also, in our study we worked with more than five cities which overcome the research gaps of previous studies.

3. Different Meteorological Parameters of Our Study

Meteorological variables are fundamental in interpreting and predicting the dynamic nature of Earth’s atmosphere. These variables encompass a wide range of atmospheric conditions that shape weather patterns, climate trends and environmental responses. This chapter explores essential meteorological variables and their implications in regions like Bangladesh where monsoons and climate-sensitive activities significantly influence agriculture, water resource management, and public health planning.

By examining key variables such as rainfall, temperature (maximum and minimum), relative humidity, wind speed, cloud coverage, and bright sunshine, this study provides insights into atmospheric patterns and their regional impacts particularly the dynamics of the monsoon season in Bangladesh. Given the critical role of these parameters in weather forecasting, statistical data analysis and the application of advanced predictive models are essential for enhancing forecasting accuracy and creating reliable climate models. This study focuses on the following seven meteorological variables such as rainfall, maximum temperature, minimum temperature, relative humidity (RH), windspeed, cloud coverage and bright sunshine

Each of these variables holds unique importance in atmospheric studies and has specific applications in predicting seasonal weather patterns and climate behaviours, particularly for tropical regions.

4. Materials And Methods

The meteorological data used in this study were obtained from the NASA POWER (Prediction of Worldwide Energy Resources) database for eight divisional cities of Bangladesh: Dhaka, Khulna, Rajshahi, Rangpur, Chittagong, Sylhet, Barishal, and Mymensingh. A total of seven climate features were considered as input parameters: Maximum Temperature (°C), Minimum Temperature (°C), Rainfall (mm), Relative Humidity (%), Wind Speed (m/s), Cloud Coverage (%), and Bright Sunshine (hours). The target variables selected for forecasting were Maximum Temperature, Rainfall, and Relative Humidity as these parameters show strong influence on both climatic shifts and sectoral vulnerability in agriculture and health. Prior to model training correlation analysis was conducted to quantify the linear relationships among the meteorological variables and to assess their joint impact on the prediction targets. The dataset was then processed through normalization using Min-Max scaling to ensure stable gradient propagation during training. Instead of applying a traditional random train-test split, the model was trained using the complete time-series sequence maintaining its chronological integrity to prevent data leakage and preserve temporal dependencies.

Two deep learning architectures were implemented using Python. The Artificial Neural Network (ANN) model consisted of fully connected dense layers with nonlinear activation functions to capture complex feature interactions. The Recurrent Neural Network (RNN) model utilized memory-based processing to retain sequential patterns across time steps making it suitable for temporal climate data. Both models were trained using backpropagation with adaptive learning optimization. Their performance was evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2). These evaluation metrics provide complementary insights into prediction accuracy, variance distribution and overall model reliability. After comparative analysis, the ANN model demonstrated lower error scores and higher R^2 values relative to the RNN model indicating superior generalization capacity for long-term climate forecasting in the studied regions. All computations and deep learning experiments were executed in a Python environment using TensorFlow/Keras libraries, ensuring reproducibility and scalability for extended forecasting applications.

*4.1. **Artificial Neural Networks (ANN) Model***

Artificial Neural Networks (ANNs) are conceptually motivated by the working principles of the human brain. They are represented as directed networks in which artificial neurons act as processing units. Each neuron generates an output by applying a nonlinear activation function to a weighted combination of its inputs with these weights adjusted during training to enhance predictive accuracy. The network is organized into input, hidden, and output layers, enabling progressive information processing and effective pattern learning. Here are some components of ANN model.

4.1.1. Neurons

A link in an artificial neural network is called an artificial neuron. The layered design of artificial neural networks (ANNs) is similar to that of the biological neural network found in the human body. Each network node, or connection point, has the ability to process input and send output to other network nodes.

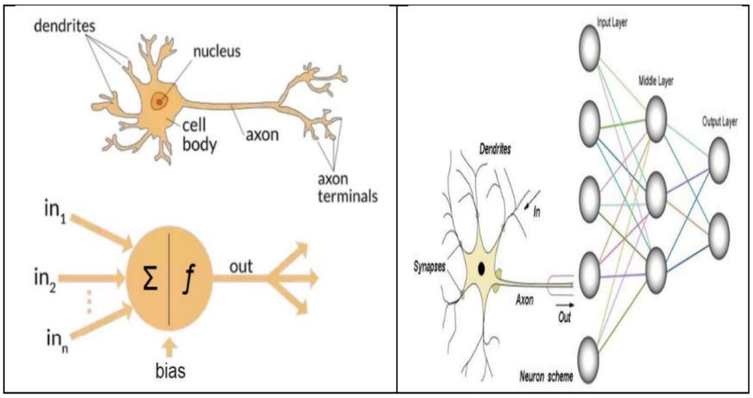


Fig 4.1. Neuron vs Neural Network

4.1.2. Connections and Weights

In an artificial neural network (ANN), weights are numerical values that correspond to the connections between neurons (or nodes) at various network levels. The strength and direction (positive or negative) of the influence that one neuron has on another are indicated by the weight that is assigned to each link between neurons.

4.1.3. Activation Function

Neural networks use activation functions as essential building blocks for understanding intricate patterns in data. It converts a neural network node's input signal into an output signal that is sent to the following layer.

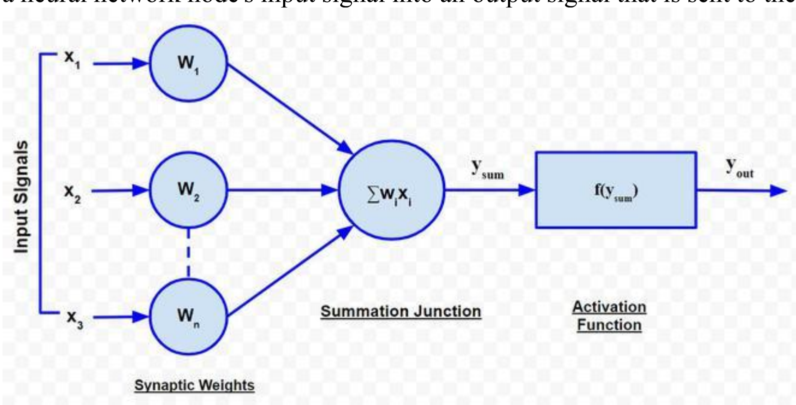


Fig 4.2. Activation function for ANN

4.1.4. Organization

Three primary layer types- the input layer, hidden layer, and output layer usually make up an Artificial Neural Network's (ANN) structure. Each neuron in the input layer represents an input feature and the sample data for the variables is placed there. ANNs can have one or more hidden layers with many neurons in each layer. Observed outputs are finally obtained in the output layer.

The hidden layer maintains the weights of the model with the activation function and the connections with the lowest error.

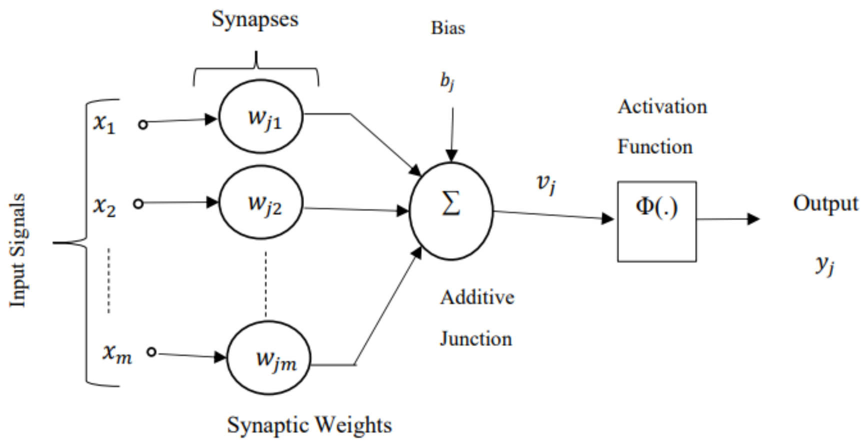


Fig 4.3. Organization of ANN

4.1.5. ANN Processing System

ANN model mainly has two parts: Training and Testing. In the training part, we have to train the data and in the testing part, we have to test some data according to the training data. In the training part, ANN adjusts the values of the weights and the biases.

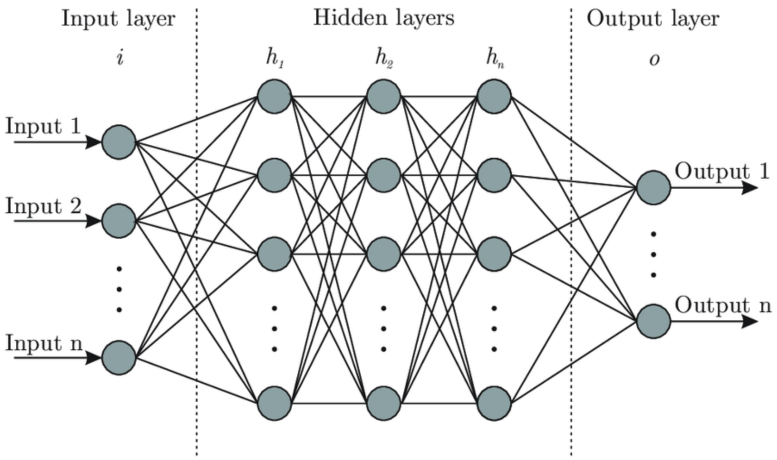


Fig 4.4. ANN Processing System.

Let, $x_1, x_2, \ldots, x_m$ are input signals in the input nodes $i_1, i_2, \ldots, i_m$ respectively which belongs in the input layer. In the single hidden layer, $j_1, j_2, \ldots, j_n$ are the nodes of the hidden layer. Now, w_{11} is the weight from i_1 to j_1 , w_{12} is the weight from i_1 to j_2 ,…, w_{1n} is the weight from i_1 to j_n . Similarly, w_{21} is the weight from i_2 to j_1 , w_{22} is the weight from i_2 to j_2 ,…, w_{2n} is the weight from i_2 to j_n and so on. $\theta_1, \theta_2, \ldots, \theta_n$ are the biases of each node of the hidden layer. Then the weighted sums from the input layer to each node of the hidden layer are expressed as,

$$v_{ij} = \theta_j + \sum_{j=1}^{n} w_{ij} x_i \tag{4.1}$$

So, the input of each output node will be the weighted sum and the output of each output node will be:

$$Y_k = \frac{1}{1+e^{-v_{jk}}} \tag{4.2}$$

The training portion of the network is primarily responsible for estimating weight and bias. The initial value of the biases and weights is often taken to be 0. There are two guiding ideas in training:

- Iterative error minimization: weights are updated using neuron-specific errors.
- The process of back-propagation involves calculating errors from the final layer to the initial layer.

The equations for weight estimations are respectively:
For output nodes,

$$w_{jk}^{new} = w_{jk}^{old} + lr*(error)*y_k \tag{4.3}$$

$$error = y_k(1-y_k)* \text{ (target output- } y_k \text{)} \tag{4.4}$$

Where, y_k is the obtained output before training the network
For hidden nodes,

$$w_{ij}^{new} = w_{ij}^{old} + lr*(error)*y_k \tag{4.5}$$

$$error = y_k(1-y_k)*\sum_i error_i w_{ij}^{old} \tag{4.6}$$

Once these equations are executed, then the weights are estimated by the following equation:

$$w_{jk}^{new} = w_{jk}^{old} + (1-m)*lr*error*y_k + m(w_{jk}^{old} - w_{jk}^{older}) \tag{4.7}$$

Where lr is the learning rate which ranges from 0 to 1 and m is the momentum which ranges from 0 to 1
This process will be continued until the weights are estimated with minimum error.
When the training is over, the model tests the system with some data to test whether it gives almost the same outputs which are observed in many systems. This is the system by which the model works.
How many data are tested or trained is not fixed? But most of the researchers divided the data set into two parts: for the number of data to be trained is, $N_{tr} = (\frac{1}{4} \div \frac{1}{3})N$, where N = total amount of data. The number of data to be tested is, $N_{ts} = (N - N_{tr})$.

4.2. Recurrent Neural Networks (RNN) Model

Recurrent Neural Networks (RNNs) are a specialized class of artificial neural networks (ANNs) designed to process sequential or time-series data effectively. Unlike traditional feed forward neural networks which process each input independently without considering prior information. RNNs are uniquely structured to capture and utilize the interdependencies between elements within a sequence. This ability makes RNNs particularly well-suited for tasks where context and order are essential such as natural language processing (NLP), speech recognition, and machine translation.

4.2.1. Types of Recurrent Neural Network (RNN)

There are several different types of RNNs, including:

- Simple Recurrent Networks (SRNs)
- Long Short-Term Memory (LSTM)
- Gated Recurrent Units (GRUs)

For the current research, the Long Short-Term Memory (LSTM) model has been chosen. Below is a brief description of the different types of RNNs:

4.2.1.1. Simple Recurrent Networks (SRNs)

Simple Recurrent Networks (SRNs) are a straight forward type of RNN known for their simple architecture and ease of training. The basic structure of a SRN involves a single hidden layer that is connected to itself via a feedback loop. This feedback mechanism is key to enable the network to learn and represent temporal dependencies within the data.

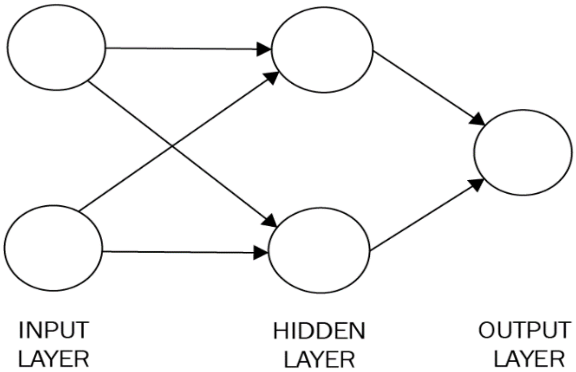


Fig 4.5. Simple Recurrent Networks (SRNs)

4.2.1.2. Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) networks are an advanced type of RNN architecture developed to address the vanishing gradient problem inherent in traditional RNNs. In standard RNNs, error gradients become very small when back propagated through multiple layers, preventing the network from effectively learning long-term dependencies.

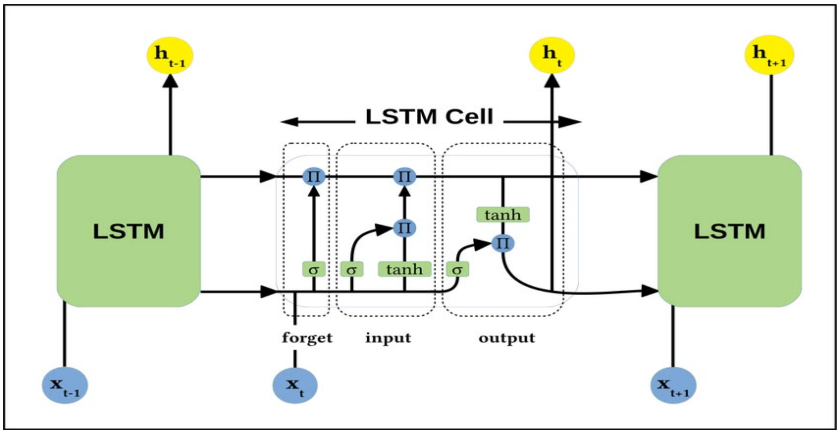


Fig 4.6. Long Short-Term Memory (LSTM) model

4.2.1.3. Gated Recurrent Units (GRUs)

Gated Recurrent Units (GRUs) represent a streamlined and computationally efficient variation of recurrent neural network (RNN). GRUs provide a simpler alternative to Long Short-Term Memory (LSTM) networks while still achieving strong performance across a diverse array of applications. These applications include areas such as speech recognition, machine translation and natural language processing where sequence data and temporal dependencies are critical.

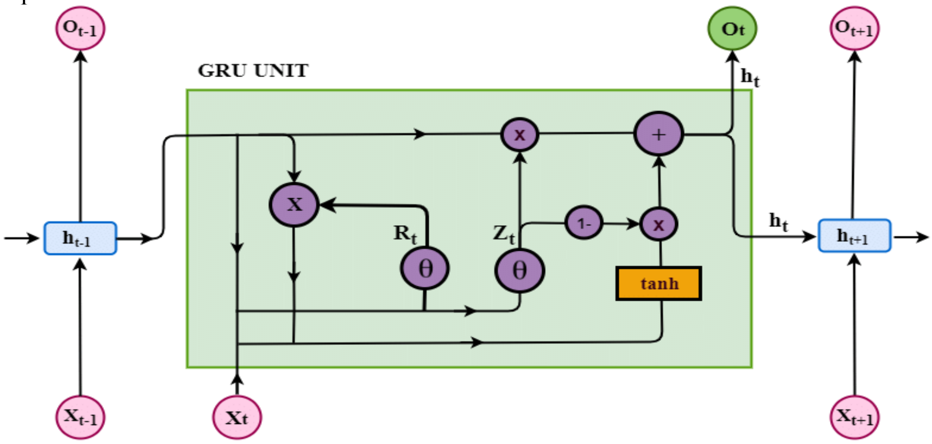


Fig 4.7. The Architecture of Basic Gated Recurrent Units (GRUs)

4.2.2. Organization

The input layer, hidden layer, and output layer are the three main layers that make up a standard Recurrent Neural Network (RNN) model. Sample data variables are stored in the input layer, and weighted outputs from earlier layers are incorporated into the hidden layer, which uses activation functions to process the weighted sum of inputs. Lastly, observable results are produced by the output layer.

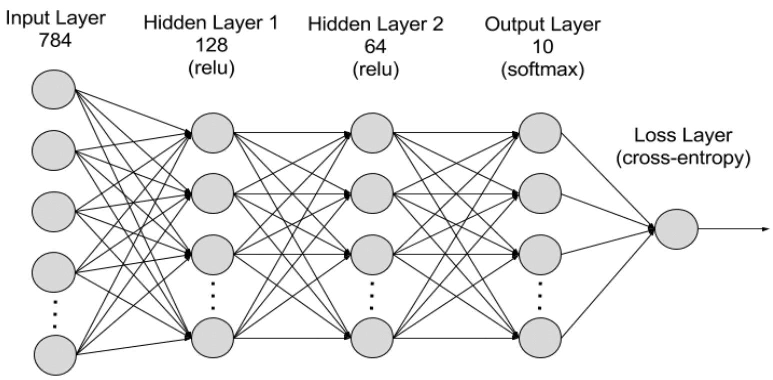


Fig 4.8. Structure of Recurrent Neural Networks (RNNs)

Recurrent Neural Network (RNNs) are defined with the given equation-

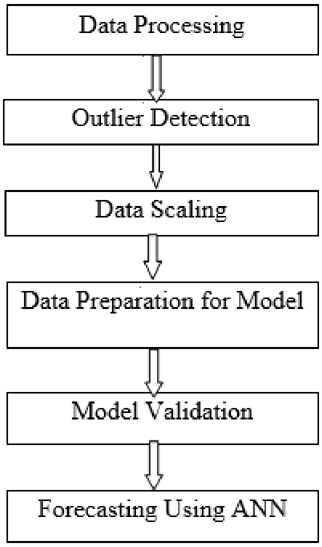
$$h_t = f(w_h h_{t-1} + w_x x_t + b_h) \tag{4.8}$$

Where,

- h_t is the hidden state at time step t
- w_h is the weight matrix connecting the hidden stage from the previous one
- w_x is the input weight
- f is the activation function

5. Data Processing

For any numerical data, we need to process them for further use. So, we followed the given process.



5.1. Handling Missing Values

In real-world observational datasets specially those collected over long periods missing values are almost unavoidable. If these missing observations are not properly addressed they may introduce bias, reduce statistical power and adversely affect model performance. Therefore, an appropriate missing-value handling strategy is a crucial pre processing step prior to model development. Missing data points were imputed using suitable statistical techniques to ensure no gaps in the dataset.

$$x_n = x_{n-1} + \frac{t - t_{n-1}}{t_{n+1} - t_{n-1}} * (x_{n+1} - x_{n-1}) \quad (5.1)$$

Where,

- $x_{n-1} =$ the last observed value before n
- $x_{n+1} =$ the first observed value after n
- t_{n-1} and t_{n+1} are the time points corresponding to x_{n-1} and x_{n+1}.

5.2. *Pearson Correlation Coefficient*

- It measures the linear relationship between two variables. It gives a value between **-1 and +1**.
- **+1** → Perfect positive linear correlation (both increase together)
- **0** → No linear correlation
- **–1** → Perfect negative linear correlation (one increases while the other decreases)

It is calculated using:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 (Y_i - \bar{Y})^2}} \quad (5.2)$$

Where,

- X_i and Y_i are data value
- $\bar{X}$ and $\bar{Y}$ are the means of the respective variables**.**

5.3. Data Normalization

Normalization is a common pre processing step in machine learning and data science. It involves scaling data so that it falls within a specified range, typically between 0 and 1 or -1 and 1. It is crucial to emphasize that the selection of the Pearson correlation coefficient as the statistical measure in this study was underpinned by the recognition that our dataset exhibits deviations from a normal distribution.

$$X_N = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{5.3}$$

Where,

- X_N is the normalized value
- X is the original value
- X_{max} *and* X_{min} are maximum and minimum value of the feature

5.4. Mean Squared Error (MSE)

Mean Squared Error (MSE) measures the average of the squared differences between the observed (actual) values and the corresponding predicted values generated by a model. By squaring the errors, MSE gives greater importance to larger deviations, making it particularly sensitive to large prediction errors. Better performance is indicated by a lower MSE.

It is calculated using:

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5.4}$$

Where,

- n represents the total number of observations.
- y_i denotes the actual value of the target variable at the i^{th} observation.
- $\hat{y}_i$ Indicates the predicted value of the target variable for the i^{th} observation.

5.5. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) quantifies the average magnitude of errors between observed and predicted values without considering the direction of the errors. Unlike squared error based metrics MAE treats all deviations equally making it more robust to the presence of outliers.

It is calculated using:

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{5.5}$$

Where,

- $\boldsymbol{n}$ represents the total number of observations.
- $\mathbf{y_i}$ denotes the actual value of the target variable at the i^{th} observation.
- $\mathbf{\hat{y}_i}$ Indicates the predicted value of the target variable for the i^{th} observation.

5.6. R-squared (R^2)

The coefficient of determination commonly known as R-squared (R^2) is a statistical measure that evaluates how well a predictive model explains the variability of the observed data. It represents the proportion of variance in the dependent variable that is captured by the model through the independent variables.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{5.6}$$

5.7. Root Mean Squared Error (RMSE)

Root mean Squared Error (RMSE) measures the square root of the average of the squared differences between observed values and model predictions. By squaring the errors before averaging RMSE assigns greater weight to larger errors making it particularly sensitive to extreme deviations.

It is calculated using:

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5.7}$$

Where,

- n represents the total number of observations.
- y_i denotes the actual value of the target variable at the i^{th} observation.
- $\hat{y}_i$ Indicates the predicted value of the target variable for the i^{th} observation.

6. Model Evaluation and Comparison

Using metrics such as MSE, MAE, R^2 and RMSE the objective is to evaluate and compare how well the RNN and ANN models predict rainfall. This comparison aids in determining which model is best for forecasting the future and in recognizing the advantages and disadvantages of each strategy. For both models, we have the evaluated MSE, MAE, R^2 and RMSE results which are listed below

Table 6.1: Comparison between ANN and RNN model

Tests	ANN model	RNN model
MSE	0.194	0.3099
MAE	0.332	0.392
R^2	7.256	6.721
RMSE	0.441	0.556

6.1. Model Selection and Justification

RNN vs. ANN: The ANN model appears to be the more effective model for rainfall prediction based on the performance criteria. Here ANN model gives better R^2 value than RNN model. Again, for the errors (MAE, MSE and RMSE) ANN gives lesser values then RNN model. Which indicates ANN emerged as the most reliable model for these predictions.

So, the superior MSE, MAE, and RMSE of the ANN model imply that it is more effective in reducing prediction mistakes.

7. Result And Discussion

In our work we used data of seven features then we predicted three (Rainfall, Relative Humidity and Max Temperature) and finally calculated the sequence by which they will change in future and also compared among the eight divisional cities. Now we will discuss about those below.

7.1. Khulna

Khulna is located in the south western part of Bangladesh. Khulna's climate brings hot, humid summers, heavy rains in the monsoon, and mild, cool winters, with high humidity year-round due to its location near the Sundarbans and the rivers.

7.1.1. Maximum Temperature

The city's tropical climate and lower rainfall during the pre-monsoon period contribute to these elevated temperatures. Seasonal variations, along with its geographical location in south western Bangladesh, influence the temperature trends.

7.1.1.1. Correlation

Correlation is a statistical measure which indicates the strong and weak relationship between two variables. It is often represented by the correlation coefficient (r), which ranges between -1 to 1. A positive correlation means both variables move in the same direction, while a negative correlation indicates they move in opposite directions.

Table 7.1: Correlation between Max Temp and other features.

Rainfall	0.413828
Min Temp	0.669007
Relative Humidity	-0.064905
Wind Speed	0.434350
Cloud Coverage	0.092781
Bright Sunshine	0.006203

The correlation value is 0.413828 between maximum temperature and rainfall. There is a moderate positive relation. When maximum temperature increases, rainfall increases. The relation between maximum temperature and minimum temperature is moderate positive because the correlation value is 0.669007.

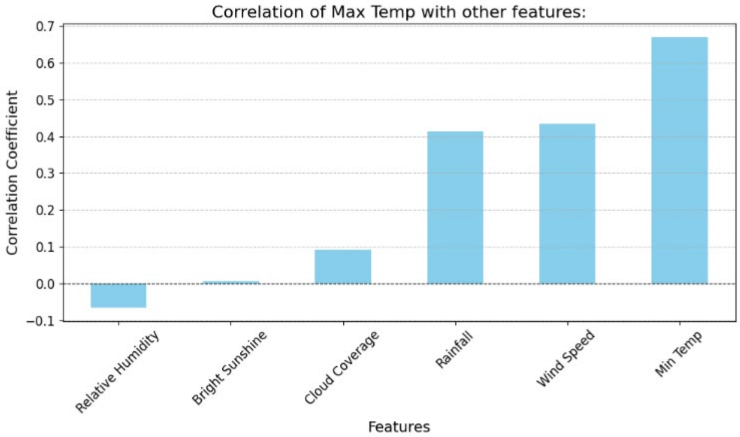


Fig 7.1. Correlation of Maximum Temper with Other Features

The correlation value with relative humidity is -0.064905 which is very close to zero means that there is little to no linear relationship or very weak negative relation. The correlation value between the variables maximum temperature and wind speed is 0.434350. It suggests a weak to moderate relationship. As maximum temperature increases wind speed increases as well. The relation with cloud coverage and bright sunshine is extremely week or negligible as the value is very close to zero.

7.1.1.2. Predicted Temperature

This graph compares the original and forecasted maximum temperature data.

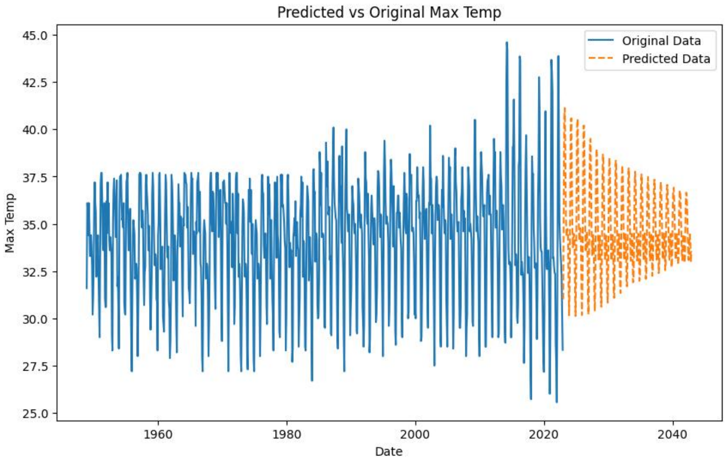


Fig 7.2. Comparison of Predicted and Maximum Temperature Data

Significant oscillations may be seen in the original data (blue lines), which represent seasonal or annual variations in the maximum temperature across decades. It displays a significant degree of annual temperature fluctuation, which is indicative of the inherent climatic unpredictability. The forecasted data graph (orange dashed lines) from 2023 to 2042 is less erratic and smoother than the original data. With incremental increases in the higher range as 2040 draws near, the forecasted temperatures seem to fall between about 30°C and 40°C.It implies that throughout the ensuing decades, temperatures will progressively increase.

7.1.2. Rainfall

July and August are typically the wettest months, driven by monsoonal winds and occasional cyclonic influences from the Bay of Bengal. Pre-monsoon and post-monsoon rains are comparatively lighter, with a distinct dry season in winter.

7.1.2.1. Correlation

Correlation is a statistical measure which indicates the strong and weak relationship between two variables. It is often represented by the correlation coefficient (r)**,** which ranges between -1 to 1. A positive correlation means both variables move in the same direction, while a negative correlation indicates they move in opposite directions.

Table 7.2: Correlation between Rainfall and other features.

Max Temp	0.413828
Min Temp	0.564440
Relative Humidity	0.400493
Wind Speed	0.362655
Cloud Coverage	0.133887
Bright Sunshine	-0.588159

The correlation value between rainfall and maximum temperature is 0.413828. It indicates a weak to moderate positive linear relationship between them.

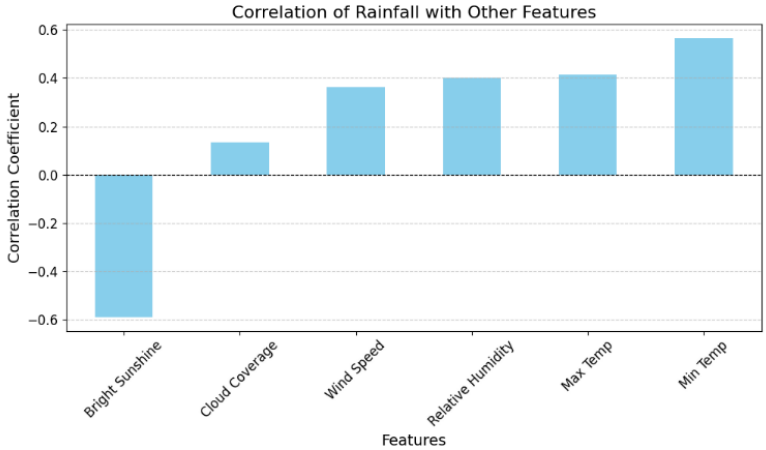


Fig 7.3. Correlation of Rainfall with Other Features

If rainfall increases maximum temperature also increases though the relationship not very strong. The correlation value with minimum temperature is 0.564440 which is also a moderate positive relationship. The relation of rainfall with relative humidity and wind speed is also weak positive relationship. The correlation value is 0.133887 which suggests a very negligible relation between them. There is inverse correlation between rainfall and bright sunshine.

7.1.2.2. Predicted Rainfall

Original rainfall data (from 1950 to 2022) and projected data (from 2023 to 2042) are displayed on the graph. Heavy rainfall occurrences are indicated by notable spikes in the measured rainfall, which ranges from 0 mm to around 800 mm. the forecast rainfall seems to be significantly lower.

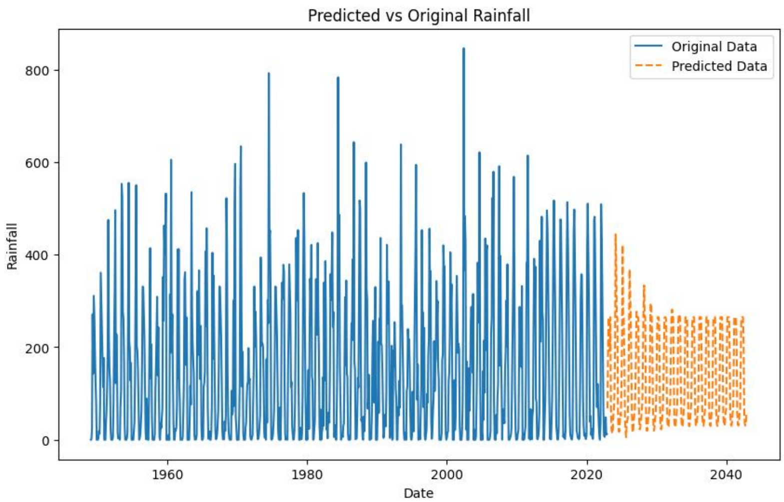


Fig 7.4. Comparison of Predicted and Original Rainfall Data

With values usually ranging from 100 mm to 300 mm, the forecast rainfall seems to be significantly lower. Less variation suggests that the model anticipates a more consistent, modest amount of precipitation.

7.1.3. Relative Humidity

The humid conditions are primarily due to the heavy rainfall and proximity to water bodies, such as the Sundarbans mangrove forest. Humidity levels tend to be lower during the cooler winter months, but remain relatively high compared to other regions in Bangladesh.

7.1.3.1. Correlation

Correlation is a statistical measure that indicates the strength and direction of the relationship between two variables. It is often represented by the correlation coefficient (r), which ranges from -1 to 1.

Table 7.3: Correlation of Relative Humidity with others

Rainfall	0.400493
Max Temp	-0.064905
Min Temp	0.575390
Wind Speed	0.111616
Cloud Coverage	0.037527
Bright Sunshine	-0.642830

The correlation between relative humidity and rainfall is 0.400493 which indicates a positive weak relationship. The relationship is negative between relative humidity and maximum temperature but the value is close to zero which is negligible. The relation with minimum temperature is positive but not strongly. The relation between humidity and wind speed is positive but very weak. The correlation value is -0.642830 indicates a moderate to strong negative relationship.

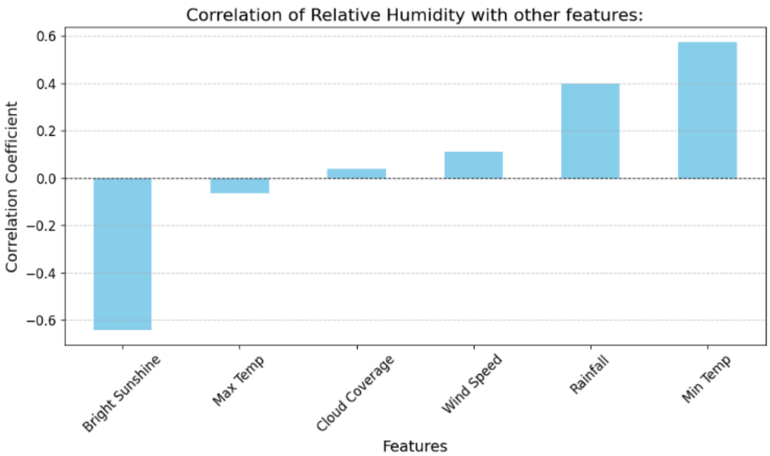


Fig 7.5. Correlation of Relative Humidity with Other Features

7.1.3.2. Predicted Relative Humidity

Original relative humidity data (from 1950 to 2022) and projected data (from 2023 to 2042) are displayed on the graph. Original data displays high variability, with some sharp decreases and fluctuations and predicted data displays smoother, cyclic patterns without the extreme fluctuations seen in the original data. The original data shows more irregularity, likely due to real-world weather variability. The predicted data suggests a seasonal pattern of increasing and decreasing relative humidity, indicating the model captures periodic trends like seasonal effects.

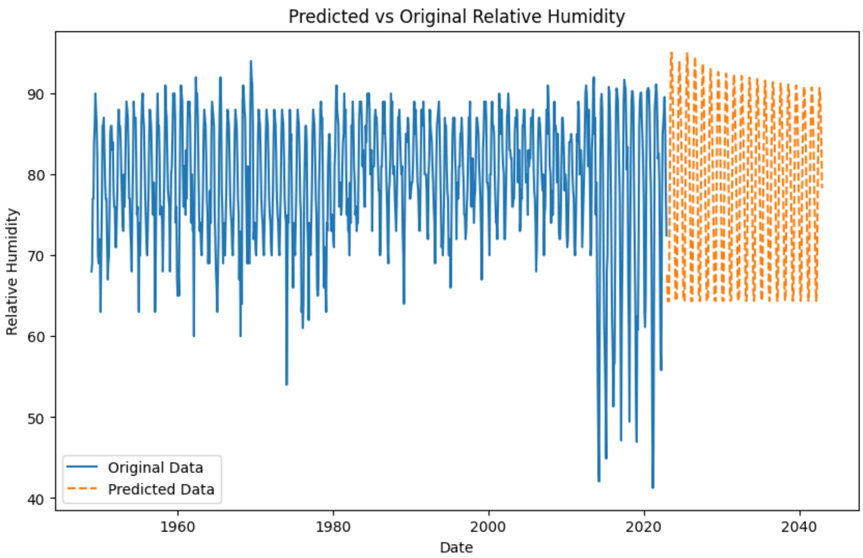


Fig 7.6. Comparison of Predicted and Original Relative Humidity Data

Conclusion

This study employed Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) to forecast Maximum Temperature, Rainfall, and Relative Humidity for eight divisional cities of Bangladesh over the period 2023–2042. The results reveal clear spatial variability and distinct regional climate patterns. Cities including Khulna, Dhaka, Rajshahi, Rangpur, and Chittagong are projected to experience rising temperatures**,** ranging from 0.45°C in Rajshahi, 0.76°C in Dhaka, alongside declining rainfall from 3.17 mm in Rajshahi, 9.25 mm in Dhaka, and decreasing relative humidity from 0.14% in Khulna to 0.58% in Dhaka**.** These trends suggest potential challenges related to heat stress, water scarcity, and agricultural productivity. In contrast, Sylhet and Barishal are expected to experience temperature decreases of approximately 0.43°C and 0.71°C, respectively, while their rainfall increases by 8.68 mm in Sylhet and 5.90 mm in Barishal, and relative humidity rises by 0.36% in Sylhet and 0.14% in Barishal indicating wetter conditions despite lower temperatures. Mymensingh shows a unique pattern, with temperature increasing by 0.61°C**,** rainfall by 3.90 mm**,** and relative humidity by 0.14% demonstrating simultaneous growth in all key parameters.

Overall, three distinct regional patterns emerge:

1) Rising temperature with declining rainfall and humidity in Khulna, Dhaka, Rajshahi, Rangpur, and Chittagong.

2) Decreasing temperature with increasing rainfall and humidity in Sylhet and Barishal**.**

3) Simultaneous increases in temperature, rainfall, and humidity in Mymensingh. These insights highlight the necessity of city-specific climate adaptation strategies to address regional vulnerabilities. While, the models demonstrate strong predictive capability, this study is limited by its monthly temporal resolution and the absence of national-level aggregation. Future work could enhance forecast granularity, explore daily predictions, and provide a comprehensive nationwide climate assessment.

The findings of this study have practical significance for climate adaptation planning in Bangladesh. The city-wise variations in temperature, rainfall and relative humidity can assist policymakers and planners in developing region-specific strategies for agriculture, water management, urban development and public health. Such localized insights are more effective than uniform national assessments. Future research may improve this work by using daily-scale data, incorporating additional climatic variables and applying advanced deep learning models to enhance prediction accuracy and broader applicability.

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