

FORECASTING TEMPERATURE TRENDS IN SYLHET, BANGLADESH: A COMPARATIVE ANALYSIS OF MACHINE LEARNING AND TIME SERIES MODELS

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ABSTRACT

Climate change is a big problem for the world, because increasing temperatures are causing extreme weather to happen more often and become more severe. Bangladesh is particularly vulnerable to these impacts, making accurate temperature forecasting a critical need for vital sectors like agriculture, energy, and tourism. This study looks at how well different machine learning (ML) models perform compared to traditional time-series models for predicting temperature in Sylhet, Bangladesh, to help identify local climate change. This study utilized time series models, including the Autoregressive Integrated Moving Average (ARIMA) and ARIMAX, and ML models such as k-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF), Adaptive Boosting (AdaBoost), and an Artificial Neural Network (ANN). The analysis was performed on a 57-year dataset from January 1, 1965, to December 31, 2021, with trends examined using the Mann-Kendall test. Model performance was evaluated using seven indicators: RSR, MAE, R², RMSE, Index of Agreement(d), NSE, and PBIAS (%). The results showed that the ANN model predicted temperature better than all the other models. This means that advanced ML methods like ANN can be very useful for forecasting temperature, which is essential for planning how to reduce and adapt to climate change in vulnerable areas.

Keywords: *Global warming, Climate change, Temperature, forecasting, Sylhet*

1. INTRODUCTION

Climate change has become a major global concern since it is affecting substantially all the plants and animals on the planet (Tol, 2013). Reducing the effects of climate change is one of the biggest challenges for humanity. Even though predicting climate change is difficult, scientists agree that it causes many serious problems, such as harm to ecosystems, loss of biodiversity, soil erosion, extreme heat, rising sea levels, and overall global warming. It also affects the economy, human health, food security, and energy systems (Abdel-Aal, 2004; Pachauri et al., 2014). In particular, predicting temperature is very important because it is needed in many fields, involving agriculture, industry, energy, the environment, tourism, and others (Li et al., 2016). Weather forecasting is very important for Bangladesh's economy because agriculture makes up about 20% of the country's GDP, around 70% of people live in rural areas, and 60% depend on farming for their livelihood. Farming exports account for 13–18% of GDP. Variations in rainfall, humidity, wind speed, and temperature strongly affect agriculture and, consequently, the national economy (Islam & Uyeda, 2007; Khan et al., 2015; Rahman et al., 2017; Rina et al., 2012). Therefore, predicting temperature correctly is important for projection infrastructure, insurance, energy use, and business decisions (Smith et al., 2007).

The most influential climate elements were evaporation, minimum humidity, and sunshine duration (Sawan, 2018). Due to high rates of evaporation, Australia loses over 40% of its entire water storage capacity each year (Helfer et al., 2012). Dew point temperature is the most general measure of humidity and helps predict both relative and specific humidity. When the dew point changes, the relative humidity also tends to change. The Clausius–Clapeyron states that for every 1°C increase in temperature, the air can hold about 7% more moisture, mainly because of global warming (Mortuza et al., 2014) (Schaller et al., 2016). A worldwide rising trend of cloud cover, near-surface humidity, and precipitation has been correlated with higher temperatures and enhanced evapotranspiration (Huntington, 2006). In places where nighttime temperatures converted to more than 0.5°C warmer than daytime temperatures, cloud cover, humidity, and rainfall all increased. But in areas where daytime temperatures increase more than 0.5°C above nighttime temperatures, cloud cover, humidity, and rainfall went down (Cox et al., 2020). In Sweden, precipitation rose by 6% and mean temperature by 0.8°C between 1961–1990 and 1991–2000, changes largely driven by anthropogenic forcing (Räisänen & Alexandersson, 2003). Sea level variations are also influenced by atmospheric circulation and CO₂ concentration (Stammer & Hüttemann, 2008). For Bangladesh, temperature rising trend can effect on drought severity (A. H. Nury et al., 2025).

Studying and predicting time-based data is essential for identifying patterns in rainfall, humidity, and temperature (A. Nury et al., 2013). To predict temperature, people commonly use time series models like Auto Regressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), and Seasonal Auto-Regressive Integrated Moving Average (SARIMA) (Bang et al., 2019; Colak et al., 2015; Dimri et al., 2020; Shakti et al., 2017). ML techniques, such as support vector machines (SVM), artificial neural networks (ANN), multivariate discriminant analyses (MDA), etc., are effective modeling tools for establishing a connection between inputs and outputs because they are not constrained by the same presumptions as statistical techniques (such as ARMA and ARIMA) (Chou & Tran, 2018). By using different input features, such as past temperature, humidity, sunlight, rainfall, and wind speed, ML models can improve their ability to forecast temperature accurately. (Cifuentes et al., 2020). ML methods for time-series prediction are becoming more accurate and useful, especially when examining climate change (Azari et al., 2022). Linear Regression is another well-known ML technique used to solve issues with one or more variables (Ahmadi et al., 2022; Marill, 2004; Mehri et al., 2021). K-nearest Neighbor (KNN) is a nonparametric ML technique, has a long history of application in ML literature to address regression issues. SVM regression is another method used to find the connection between input variables and the output (Liu et al., 2013; Wang et al., 2010). ANN is very popular and widely used because it can learn complex, nonlinear patterns between input features and the target values. It has been used to solve several ML issues in various fields (Fotovvati et al., 2020; Najah et al., 2013; Singh et al., 2009). An Iranian study compared six machine learning methods: Linear Regression, k-Nearest Neighbor, Support Vector Machine, Artificial Neural Network, Random Forest, and Adaptive Boosting for predicting average daily temperature. Among them, the Artificial Neural Network performed best in both training and prediction accuracy (Azari et al., 2022). Similarly,

a review by Tran et al. (2021) highlighted that ANN models are fast and effective for forecasting air temperature, though there is still no clear agreement on which ANN technique works best.

Bangladesh is among the most vulnerable countries to climate change due to its low elevation, dense population, and dependence on natural resources (Al-Amin et al., 2013). About one-third of Bangladesh could be submerged by a one-meter sea level rise, displacing 25–30 million people (Choudhury et al., 1997). Climate model projections and long-term temperature and rainfall records indicate that global warming and greenhouse effects will continue to raise sea levels and intensify climatic changes in the region. These shifts in temperature and rainfall directly harm Bangladesh's socio-economic stability through increased surface warming, floods, and coastal inundation (Choudhury et al., 1997).

The global average temperature is projected to rise by 1.5°C by mid-century and 2.5°C by its end. Correspondingly, sea levels may rise by about 14 cm in 2030, 32 cm in 2050, and 88 cm in 2100, inundating 8, 10, and 16 percent of Bangladesh's entire landmass, respectively. Many coastal and island regions in Khulna, Barisal, and western Chattogram lie within one meter of sea level, making them highly vulnerable to saltwater intrusion and unsuitable for cultivation (Awal & Khan, 2020). Therefore, accurate local temperature modeling using global climate factors is essential to reduce the impacts of global warming. Although a few studies (Pour et al., 2018; Shafin, 2019; Zaman, 2018) have documented the application of machine learning techniques on meteorological variables, no study has used machine learning models that this study considers to investigate global warming in Bangladesh. The present study, filling in the aforementioned research gap, is mainly aimed at investigating global warming (temperature) in Bangladesh for almost 57 years based on daily data collected from different public sources. Specifically, it seeks to apply the classical time series model ARIMA, ARIMAX to the temperature data, and to compare machine learning approaches to explore the effects of different influences on global warming in Bangladesh. This study also intends to forecast the temperature as well as the concentration of several climate variables for the next several years and visualize the real, predicted, and forecasted data so that the actuality can be understood briefly.

2. METHODOLOGY

2.1 Study Area

Sylhet, located in north-eastern Bangladesh at 24.8917°N and 91.8833°E, is covered by the Sylhet meteorological station along with its nearby areas. This area is rich in natural resources, especially its small hill areas (tilas), which contain over 150 tea estates. The wetlands in this area support a growing population that depends on them for their livelihood, and they also offer an important habitat for many types of wildlife.

2.2 Data Collection

The raw data collected from BMD and ERA5 (hourly data) needed a lot of cleaning before it could be used. It had to be converted from a semi-structured format into a proper structured dataset suitable for modeling. After preprocessing, each dataset involved four key factors: wind speed, rainfall, humidity, and temperature (both minimum and maximum). This study used the cleaned dataset to build forecasting models and then compared the results to identify which model performed best. The variables included in the dataset are rainfall (in millimeters), humidity (as a percentage), wind speed (in km/h), and temperature (in °C). In general, long-term weather forecasting is grouped into four main methods: (a) periodicity approach, (b) correlation approach, (c) extended synoptic approach, and (d) dynamical approach (Rajeevan et al., 2007). BMD is a government agency for weather prediction in Bangladesh. In 2007 BMD first introduced a statistical forecast system based on an ensemble technique (Andrade & Bessa, 2017; Mahabub et al., 2019). Although their predictions were acceptable, they were always dependent on some specific predictors. However, it was tried to be taken one step forward through the research.

2.3 Statistical Methods

In this study, several statistical and ML models were used to create time-series forecasts. ARIMA is a traditional statistical method that forecasts future values by using past data and past errors. It works well with stationary data after removing trends or seasonality patterns (*Time Series Analysis*, n.d.). ARIMAX is an improved version of ARIMA that adds extra factors, such as rainfall or humidity, to make predictions more accurate. In ML, the KNN method forecasts a value by finding past cases that are most similar and then averaging their values. (Akter et al., 2009). The SVM model builds a boundary or function that best fits the data and helps to make accurate predictions, even when the relationship between variables is complex (Yang et al., 2002). The Random Forest method combines many decision trees and takes their average result to reduce errors and overfitting (Breiman, 2001). The AdaBoost (AdB) technique improves prediction accuracy by giving more importance to the data points that are predicted incorrectly, allowing the next model to focus more on them (Duan et al., 2019; Mousavi et al., 2019). Finally, ANN works through layers of related nodes (neurons) and can understand complex, non-linear patterns in the data. It uses the RELU activation function, which helps the model learn quickly and perform better by keeping only positive values and ignoring negative ones. (Hastie et al., 2001).

3. ILLUSTRATIONS

3.1 Time Series Models Diagnostics

3.1.1 ARIMA:

ARIMA Modeling process starts with observing the data over time. In this case, visualizing the temperature against time gives us a clear indication of the trend.

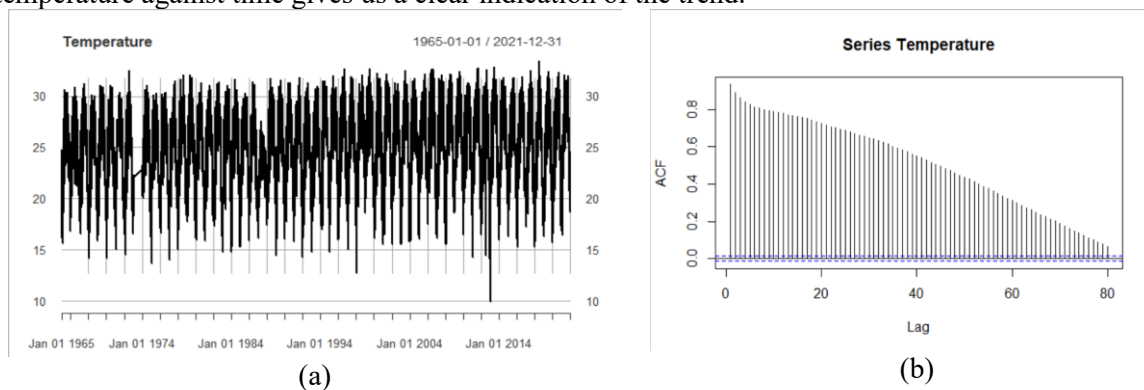


Figure 4.1a and 4.1b: Trend of Temperature over time and Autocorrelation plot

In the next step, stationarity of data needs to be checked. The autocorrelation plot shows a slow decay which means the data is clearly not stationary. This study performs the differences 2 times to make the data stationary. After applying differencing, the data becomes stationary, and the autocorrelation quickly declines close to zero after one or two lags. The Augmented Dickey–Fuller test also confirms stationarity, which shows a p-value of 0.01 after differencing.

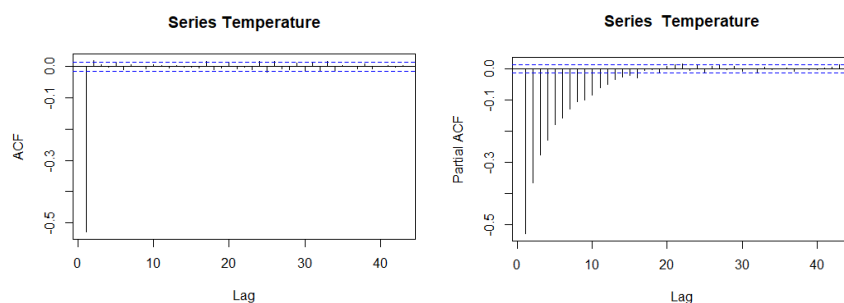


Figure 4.1c: Autocorrelation and Partial autocorrelation plot after differencing.

Table 4.1a: Augmented Dickey-Fuller Test after differencing.

Augmented Dickey-Fuller Test	
Alternative Hypothesis: Data is stationary	
Dickey-Fuller	-54.818
Lag order	27
p-value	0.01

Once the data became stationary, the ARIMA model could be estimated. ARIMA applies three parts: autoregressive order (p), differencing order (d), and moving average order (q). In this research, the differencing order (d) was already found to be 2. The values of p and q were identified by looking at the ACF and PACF plots. Based on this, the selected ARIMA model was (1, 2, 2). This model was chosen because it had the lowest Akaike Information Criterion (AIC) value, which is 61687.35. After choosing the best model, the next step was to estimate its parameters, which are shown in the table below.

Table 4.1b: Estimated parameters of ARIMA (1, 2, 2) model.

ARIMA (1, 2, 2)		
AIC: 61687.35		
Coefficients	Value	Standard error
AR (1)	0.6050	0.0101
MA (1)	-1.8701	0.0064
MA (2)	0.8701	0.0064

The last step of fitting an ARIMA model is diagnostic checking. Ljung Box test shows that the model is a white noise with a p-value of 0.8246.

3.1.2 ARIMAX:

ARIMAX model requires exogenous variables. The exogenous variables of the model are ‘Total Cloud Cover’, ‘Dew Point Temperature’, ‘Evaporation’, ‘Solar Radiation’, ‘Mean Sea Level Pressure’, and ‘Wind Speed’. After adding these independent variables ARIMA (1, 2, 2) model is found to be adequate as well. The estimated parameters are given in the table below.

Table 4.1c Estimated parameters of ARIMA (1, 2, 2) model with exogenous variables.

ARIMA (1, 2, 2)		
AIC = 54672.18		
Coefficients	Value	Standard Error
AR (1)	0.3869	0.0114
MA (1)	-1.8485	0.0076
MA (2)	0.8485	0.0076
Total Cloud Cover	-0.292	0.018
Dew Point Temperature	2.4933	0.0398
Evaporation	-0.3504	0.0161
Solar Radiation	1.8987	0.0707
Mean Sea Level Pressure	-0.1920	0.0297
Wind Speed	-0.1027	0.0110

Ljung Box test shows this model is also a white noise with p-value of 0.1306.

3.2 Machine Learning Models Diagnostics

3.2.1 Data Multicollinearity

Specific assumptions must be corroborated in the data before machine learning algorithms are applied to a data set. It is crucial to first determine whether there is any relation between the features and the target, as well as between the features themselves. The collinearity between the features and the intended data was assessed and displayed in Table 3.1. According to the table, the collinearity between the features was within the tolerable ranges necessary for machine-learning approaches. The collinearity between dew point temperature and mean sea level pressure exceeds the permissible range.

Table 4.2a: Features collinearity and correlation matrix.

Predictor	Total Cloud Cover	Dew Point Temperature	Evaporation	Mean Sea Level Pressure	Solar Radiation	Wind Speed
Total Cloud Cover	1.00					
Dew Point Temperature	0.73	1.00				
Evaporation	-0.08	-0.50	1.00			
Mean Sea Level Pressure	-0.70	-0.81	0.43	1.00		
Solar Radiation	0.53	0.66	-0.57	-0.79	1.00	
Wind Speed	0.46	0.30	0.12	-0.40	0.27	1.00

3.2.2 Mann-Kendall (MK) Test

Table 4.2b illustrates the MK test results for the time-series data. Because the p-value was below 0.05, the test proved that temperature and all the input variables had noticeable trends over time. Temperature, total cloud cover, dew point temperature, and mean sea level pressure all displayed positive increasing trends, as specified by the positive Kendall's τ values. In contrast, evaporation, wind speed, and solar radiation showed declining trends. Sen's Slope, which determines how fast a trend is changing, showed that temperature increased by 0.000081°C per day, clear evidence of climate change in the study area. Dew point temperature also increased at a rate of 0.000073 K per day. Mean sea level pressure had a minor but positive rise of 0.003739379 Pa per day, based on Sen's Slope.

Table 4.2b: Mann Kendall test statistics.

M-K test	Sen's Slope	Kendall's τ	p-value	alpha (α)	Test interpretation
Temperature	0.000081	0.0903	<0.01	0.05	Trend in Series
Total Cloud Cover	0	0.000679	0.88333	0.05	Trend in Series
Dew Point Temperature	7.26853e-05	0.093	<0.01	0.05	Trend in Series
Evaporation	-2.872019e-10	-0.0248	<0.01	0.05	Trend in Series
Solar Radiation	-3.561894	-0.133	<0.01	0.05	Trend in Series
Mean Sea Level Pressure	0.003739379	0.0268	<0.01	0.05	Trend in Series
Wind Speed	-3.075041e-06	-0.0227	<0.01	0.05	Trend in Series

3.3 Comparison between time series and Machine Learning Models

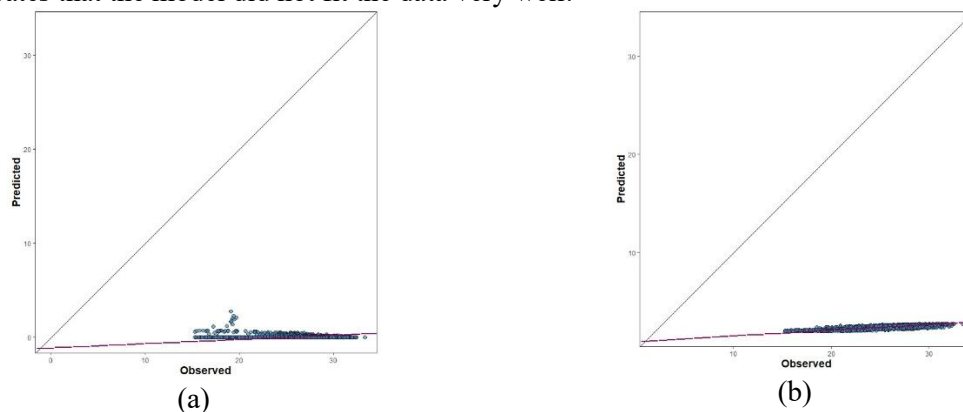
Using the offered feature data sets, classical time series models and machine learning models were utilized to predict the temperature trend in the study area. From January 1, 1965, to December 31, 2021, the combined data collection included 20819 records of daily temperature, total cloud cover, dew point temperatures, evaporation, mean sea level pressure, solar radiation, and wind speed. The training set has 18627 records from January 1, 1965, to December 31, 2015. Data from January 1, 2016, to December 31, 2021, were kept for the testing phase that determined the optimum method. To estimate the temperature for the day of concern, this study used the data from the previous day, which included daily temperature, total cloud cover, dew point temperatures, evaporation, mean sea level pressure, solar radiation, and wind speed.

Seven different performance measures were managed to check how well each trained model forecasted temperature for future dates. These included R², index of agreement (d), NSE, MAE, RMSE, percent bias (PBIAS), and the RMSE-standard deviation ratio (RSR). The results for each method are discussed in detail in this section.

Table 4.3: Models Performance on Test Dataset

Methods	RSR	NSE	MAE	Index of Agreement, d	PBIAS (%)	RMSE	R ²
ARIMA	0.5798	-3.8939	7.5739	0.7049	79.2350	8.4407	0.0040
ARIMAX	0.1091	0.8268	1.2969	0.9592	0.4844	1.5879	0.8555
KNN	0.1667	0.5953	1.9380	0.8521	5.5605	2.4272	0.6258
SVM	0.1860	0.4961	2.1586	0.8113	3.7220	2.7085	0.5156
Random Forest	0.0908	0.8798	1.0506	0.9653	22.1884	1.3226	0.9126
Adaptive Boosting	0.1131	0.8138	1.3254	0.9341	5.7312	1.6464	0.8792
ANN (ReLU)	0.0771	0.9135	0.8871	0.9742	0.6770	1.1223	0.9275

The ARIMA model was the first time-series method utilized to forecast temperature [Table 4.3]. Figure 4.3a showed the relationship between the actual values and the ARIMA model's test predictions. The plot indicates that the model did not fit the data very well.



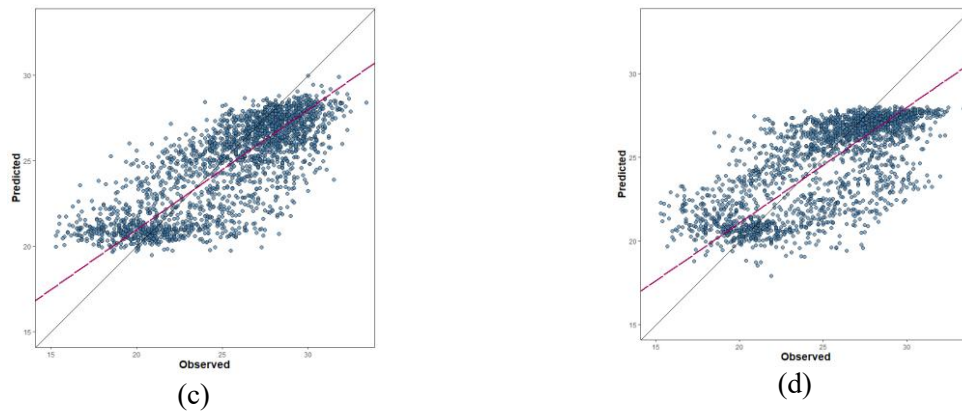


Figure 4.3a, 4.3b, 4.3c, and 4.3d: Relationship between observed and test outputs for ARIMA, ARIMAX, KNN and SVM

The ARIMAX model was applied to predict temperature, and it can work as a multiple regression model that includes autoregressive (AR) and moving average (MA) components [Table 4.3]. As shown in Figure 4.3b, the predicted values match the observed temperatures quite well, giving better accuracy than the ARIMA model.

The first ML method used was KNN. After several tests, the best performance was found when using 23 neighbors, along with the Euclidean distance and uniform weighting [Table 4.3]. Figure 4.3c showed that the KNN predictions do not fit the observed data as closely as the ARIMAX model.

For the SVM model, different settings were tested by trial and error. The software automatically selected the gamma value, and the radial basis function was used as the kernel [Table 4.3]. Figure 4.3d showed that the SVM predictions fit the data less accurately than both KNN and ARIMAX.

The Random Forest model was the first ensemble method used in this study. After several trials, 500 trees were chosen as the final model size [Table 4.3]. Figure 4.3e illustrated that the Random Forest predictions closely follow the observed temperature values, giving a much better fit than the other four models and producing highly accurate results.

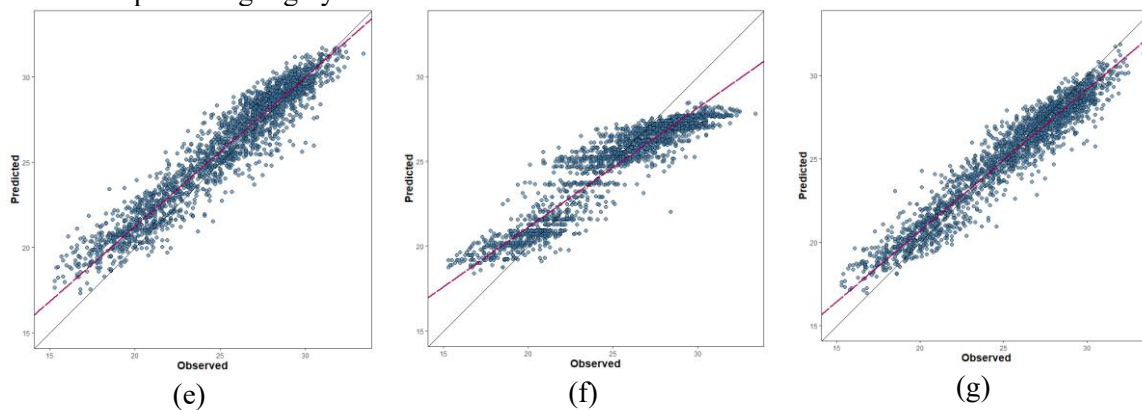


Figure 4.3e, 4.3f, and 4.3g: Observed vs. Predicted Outputs for Random Forest, AdB, and ANN Models

AdB was the second ensemble method tested in this study. The SAMME algorithm (Stagewise Additive Modeling using a Multi-class Exponential loss function) was nominated for classification, and a squared regression loss was used [Table 4.3]. Figure 4.3e showed the link between the AdB predictions and the actual temperature values. Although the model performed well and yielded results similar to the Random Forest model, its accuracy was somewhat lower.

In a neural network, the activation function transforms the combined weighted input of a node into an output value. For this research, the Rectified Linear Unit (RELU), a simple piecewise linear activation function, was employed [Table 4.3]. Figure 4.3f showed how the ANN predictions compare to the

observed temperatures. The ANN model produced highly accurate results and became the best fit among all the time series and ML methods.

Table 4.3 and the plots in **Figure 4.3g** demonstrated that all the procedures were reliable and acceptable except the ARIMA. The findings of the ARIMA model were much worse than those of the other techniques. Based on the R^2 value, the best and poorest models were the ANN approach ($R^2 = 0.9275$) and the ARIMA method ($R^2 = 0.0040$).

R^2 is typically insufficient to compare the results of different machine learning models. As a result, six additional performance indices were employed to contrast the different approaches. The values for the RSR, NSE, MAE, Index of agreement(d), PBIAS, and RSME for each approach are shown in **Table 4.3**. Except for ARIMA and SVM, all the approaches demonstrated acceptable performance, according to (D. N. Moriasi et al., 2007). According to the first group of performance scores (NSE = 0.9135, Index of Agreement = 0.9742, and $R^2 = 0.9275$), the ANN model achieved the best performance while the ARIMA model performed the worst, with much lower scores (NSE = -3.8939, Index of Agreement = 0.7049, and $R^2 = 0.0040$). Moreover, a second set of assessment measures also showed the same pattern. The ANN model again ranked highest with low error values (RSR = 0.0771, MAE = 0.8871, and RMSE = 1.1223), while the ARIMA model had the lowest results, showing much higher error values (RSR = 0.5798, MAE = 7.5739, and RMSE = 8.4407). Based only on the PBIAS indicator (PBIAS (%) = 0.6770), the ANN model performed best and ARIMA was the worst model (PBIAS(%)=79.2350). For all seven performance measures, the ARIMA approach produced the least reliable findings. Therefore, according to the seven indices ANN models produced the best results in daily temperature prediction compared to all the time series and machine learning models. Similar findings have been reported in other research that compared machine learning models for predicting temperature (Azari et al., 2022).

4. CONCLUSIONS

The Sylhet region's meteorological time series data, containing temperature, total cloud cover, dew point temperature, evaporation, solar radiation, mean sea level pressure, and wind speed, were extracted for this study. Data were collected between January 1, 1965, and December 31, 2021, or approximately 57 years. The purpose of this study was to assess the capacity of several machine learning (ML) techniques to forecast temperature in order to investigate climate change, as well as to compare them to classical time series models ARIMA, ARIMAX, etc. Two traditional time series approaches, ARIMA and ARIMAX, were employed in this study. The ARIMAX model ($R^2 = 0.8555$) is well-fitted with higher accuracy compared to the ARIMA model ($R^2 = 0.0004$). Seven indices show that ARIMAX outperforms the ARIMAX models in terms of overall performance for time series analysis (RSR, NSE, MAE,d, PAB, RMSE, RSR, and R^2). In order to predict the temperature, six machine learning techniques including kNN, SVM, Random Forest, AdB, and ANN were employed. Data from January 1, 1965, to December 31, 2015, were used as training data. Then data from January 1, 2016, through December 31, 2021, were used for testing. Except for SVM, all the methods were well-fitted, according to the test findings. The R^2 score for SVM was the lowest, coming in at 0.5156. The following six additional performance indicators were used to determine the best-fitted method: RSR, NSE, MAE, Index of Agreement (d), PBIAS (%), and RMSE. However, seven performance indicators showed that ANN was the best method compared to others for predicting temperature. Even though the ARIMAX model outperformed the ARIMA model using seven different indices (RSR, NSE, MAE,d, PAB, RMSE, RSR, and R^2). Furthermore, according to seven indices RSR, NSE, MAE,d, PAB, RMSE, RSR, and R^2) ARIMAX model outperformed both kNN and SVM machine learning approaches. Using the daily temperature, total cloud cover, dew point temperatures, evaporation, mean sea level pressure, solar radiation, and wind speed as features, it was shown that the ANN machine learning approach was the most accurate way for predicting temperature comparing six machine learning models and two classical time series methods.

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