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Machine Learning-Driven Time Series Modeling for Temperature Prediction in Bangladesh

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***Abstract*—The increasing unpredictability of temperature poses significant risks to environmental sustainability and socio-economic stability. This study focuses on forecasting temperature in eight districts of Bangladesh—Barishal, Chattogram, Dhaka, Khulna, Rajshahi, Rangpur, Mymensingh, and Sylhet—using monthly data from January 1970 to December 2022, collected from the Bangladesh Agricultural Research Council (BARC). Time series models, including SARIMA (1, 1, 1)(1, 1, 1)$_{12}$, are applied to capture seasonal patterns. Additionally, advanced machine learning models such as Long Short-Term Memory (LSTM) networks, and Random Forest regression are employed to detect non-linear trends and improve prediction accuracy. Results indicate significant seasonal fluctuations in temperature, particularly during extreme weather periods. These findings underscore the necessity for data-driven climate adaptation strategies and sustainable resource management. The combination of traditional statistical models with modern machine-learning techniques ensures robust and precise forecasting. Future research can extend this approach by including other climatic variables and using ensemble models for enhanced accuracy. This study offers critical insights for policymakers in climate-sensitive regions.**

Keywords—Temperature Variability, Modeling & Forecasting, Seasonal Trends, Time Series Analysis.

I. Introduction

Climate change is a critical global concern with significant implications for environmental sustainability, socio-economic development, and public health. Bangladesh, due to its geographical location and socio-economic conditions, is highly vulnerable to climate change, particularly temperature fluctuations. These variations directly impact agriculture, energy, and health. Given that a large portion of the Bangladeshi population relies on climate-sensitive sectors, understanding temperature trends and forecasting future variations are essential for effective policy formulation and adaptive planning [5]. The unpredictability of temperature patterns, driven by climate variability, has led to increased extreme weather events, including heatwaves and cold spells. These pose substantial risks to food security, public health, and economic stability [7]. Accurate forecasting of temperature trends is crucial for mitigating these risks and enhancing resilience. Various time series models have been employed to predict temperature variations. [1] analyzed temperature trends in Sylhet, while [4] examined the link between temperature changes and global warming, highlighting the need for reliable forecasting models. Recent advancements in machine learning have significantly improved forecasting accuracy by capturing complex non-linear patterns. [6], [2] applied ARIMA and LSTM networks to predict temperature trends in Bangladesh's coastal and northeastern regions. Additionally, [3] utilized multimodel ensemble data to assess future climate scenarios. Beyond environmental and economic impacts, temperature fluctuations affect public health. [8], [10] underscores the importance of accurate temperature forecasting for public health preparedness. As climate change intensifies, robust temperature forecasting models are essential for resilience and sustainable development in Bangladesh.

II. Materials and Methods

A. Study Area

This study focuses on Bangladesh, a tropical South Asian country divided into eight administrative divisions: Barishal, Chattogram, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet. Temperature data from meteorological stations across these divisions, sourced from the Bangladesh Agricultural Research Council (BARC), were utilized. These stations represent diverse climatic zones, providing a comprehensive analysis of temperature trends across the country.

B. Data Preprocessing

Data preprocessing involved cleaning and preparing 50 years of temperature data for accurate modeling. The following steps were applied:

1. Handling Missing Data: Stations with over 30% missing data were excluded, and the remaining gaps

were filled using interpolation techniques to maintain the integrity of the dataset.

2. Outlier Detection and Treatment: Outliers were identified using the Box Plot method. Values falling outside the range of ($Q1 - 1.5 \times IQR$ or $Q3 + 1.5 \times IQR$) were considered outliers. Errors were excluded, while valid extreme events were retained and adjusted to the nearest threshold.

3. Stationarity Test: The Augmented Dickey-Fuller (ADF) test was used to confirm stationarity, with a p-value of 0.05. Non-stationary series were transformed using differencing or detrending methods.

4. Data Splitting: The data were split into training (80%) and testing (20%) sets. The training set was used for model training, while the testing set was used for unbiased evaluation.

III. Methodology

This study applied four algorithms—ARIMA, SARIMA, GARCH, and LSTM—to model and forecast temperature trends in Bangladesh. Each algorithm was selected for its ability to address different characteristics of time-series data, enabling a comprehensive analysis of climatic variations.

A. ARIMA, SARIMA, and GARCH Forecasting

The ARIMA (Auto Regressive Integrated Moving Average), SARIMA (Seasonal ARIMA), and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models are foundational in time series forecasting, offering solutions for analyzing and predicting temperature trends in Bangladesh, where climatic patterns are complex. ARIMA models non-seasonal data with autoregressive (AR) components, differencing (I) to ensure stationarity, and moving average (MA) for residual error modeling. SARIMA extends ARIMA by incorporating seasonal patterns. GARCH models capture volatility dynamics, particularly time-varying conditional variances, which are crucial for analyzing extreme temperature fluctuations. These models address both seasonal and non-seasonal variations in temperature data.

Forecasting Steps:

- Stationarity Check: Statistical tests (KPSS and ADF) identified non-stationary characteristics such as trends and seasonality. Differencing techniques were applied when necessary to stabilize the series.
- Parameter Identification: ARIMA and SARIMA parameters were identified using ACF and PACF plots, with AIC and BIC criteria for optimal selection. For GARCH models, volatility clustering analysis guided parameter selection.
- Model Selection and Estimation: Metrics such as R^2, RMSE, MAE, and MSE assessed model accuracy. AIC and BIC ensured model parsimony, and Maximum Likelihood Estimation (MLE) was used for GARCH parameter estimation.
- Residual Diagnostics: Diagnostic tests, including the Jarque-Bera test for normality and Durbin-Watson for autocorrelation, confirmed model adequacy. Residual analysis validated the model assumptions.
- Stability Check: The Chow Forecast Test ensured model stability over time, verifying the reliability of predictions under changing conditions.
- Forecasting: Calibrated models generated point forecasts and confidence intervals. GARCH volatility forecasts identified periods of high or low temperature variability.
- Performance Evaluation: Forecast accuracy was evaluated using RMSE, MAE, and R^2. Iterative refinements improved model performance.

This methodology enhances the accuracy of temperature forecasting in Bangladesh, supporting policy planning, energy management, and risk mitigation by providing insights into climate variability and extreme weather events.

B. LSTM Forecasting

Long Short-Term Memory (LSTM) is a specialized type of recurrent neural network (RNN) designed to handle sequential and time-series data effectively. Traditional RNNs suffer from issues such as the vanishing gradient problem, which makes it challenging to capture long-term dependencies in data. LSTM addresses these issues using a unique architecture that includes a memory cell, which maintains information across time steps, helping the model retain important features for extended periods. LSTMs use three primary gates to control the flow of information: Forget gate: Determines what information to discard from the cell state. Input gate: Decides what new information to add to the cell state. Output gate: Regulates the output and updates the hidden state. These gates are controlled by learnable weights, and their outputs are generated using sigmoid and tanh activation functions, ensuring effective information flow and retention.

Forecasting Steps

- Data Preprocessing: The maximum and minimum temperature data were normalized to a scale of 0 to 1 to enhance the LSTM model's performance and ensure faster convergence during training.

- Model Construction: An LSTM model was built with one or more hidden layers. Key hyperparameters, such as the number of neurons, learning rate, and batch size, were tuned to optimize model accuracy. The model architecture was designed to capture both short-term fluctuations and long-term temperature trends.

- Model Evaluation: The trained LSTM model was evaluated using statistical metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared. The LSTM results were compared with the SARIMA/GARCH model to assess its relative performance in forecasting temperature.

- Forecasting: Using the trained LSTM model, forecasts for maximum and minimum temperatures were generated. Both short-term and long-term forecasts were produced, capturing different forecasting horizons and providing insights into immediate temperature fluctuations and long-term trends.

This approach underscores the capability of LSTM networks to model non-linear and complex temporal patterns in temperature data. By leveraging the strengths of deep learning, the study aims to provide highly accurate temperature forecasts, supporting strategic decision-making in climate-sensitive sectors such as agriculture, energy, and public health..

IV. Result and Discussion

In this study, we employed four statistical models—ARIMA, SARIMA, GARCH, and EGARCH—alongside the deep learning-based LSTM model to forecast maximum and minimum temperature trends in Bangladesh. The primary objective was to determine the most effective algorithm for capturing temporal dynamics, seasonal patterns, and temperature variability.

A. Model Performance Evaluation

The performance of each model was evaluated using four statistical metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination (R-squared). These metrics offer a comprehensive assessment of predictive accuracy and model reliability.

Model	RMSE	MSE	MAE	R^2
ARIMA	5.009	25.096	3.597	-0.87
SARIMA	1.086	1.179	0.894	0.912
GARCH	3.788	14.347	2.804	-0.069
LSTM	1.516	2.299	1.148	0.821

TABLE I. Evaluation of Max Temperature, Region: Rajshahi

Model	RMSE	MSE	MAE	R^2
ARIMA	9.011	81.202	7.073	-1.644
SARIMA	0.823	0.678	0.628	0.977
GARCH	6.78	45.976	4.912	-0.497
LSTM	1.319	1.741	0.954	0.942

TABLE II. Evaluation of Min Temperature, Region: Rajshahi

Variable	RMSE	MSE	MAE	R^2
ARIMA	2.931	8.593	2.019	-0.468
SARIMA	0.77	0.594	0.611	0.898
GARCH	2.435	5.932	1.867	-0.013
LSTM	1.245	1.55	1.012	0.729

TABLE III. Evaluation of Max Temperature, Region: Chattogram

Variable	RMSE	MSE	MAE	R^2
ARIMA	4.63	21.443	3.535	-0.163
SARIMA	0.813	0.661	0.634	0.964
GARCH	4.974	24.743	3.525	-0.342
LSTM	1.198	1.436	1.011	0.919

TABLE IV. Evaluation of Min Temperature, Region: Chattogram

Variable	RMSE	MSE	MAE	R^2
ARIMA	4.796	23.005	3.698	-1.185
SARIMA	0.936	0.876	0.767	0.916
GARCH	3.309	10.949	2.496	-0.04
LSTM	1.439	2.069	1.032	0.795

TABLE V. Evaluation of Max Temperature, Region: Khulna

Variable	RMSE	MSE	MAE	R^2
ARIMA	6.309	39.81	4.441	-0.459
SARIMA	0.826	0.683	0.628	0.974
GARCH	6.428	41.323	4.47	-0.515
LSTM	1.522	2.319	1.255	0.913

TABLE VI. Evaluation of Min Temperature, Region: Khulna

Variable	RMSE	MSE	MAE	R^2
ARIMA	3.828	14.651	2.532	-0.465
SARIMA	0.95	0.903	0.797	0.909
GARCH	3.197	10.224	2.446	-0.023
LSTM	1.638	2.684	1.359	0.722

TABLE VII. Evaluation of Max Temperature, Region: Dhaka

Variable	RMSE	MSE	MAE	R^2
ARIMA	5.222	27.272	3.97	-0.199
SARIMA	0.749	0.561	0.559	0.975
GARCH	5.379	28.938	3.981	-0.273
LSTM	1.544	2.386	1.284	0.893

TABLE VIII. Evaluation of Min Temperature, Region: Dhaka

Variable	RMSE	MSE	MAE	R^2
ARIMA	2.96	8.763	2.282	-0.021
SARIMA	1.043	1.089	0.847	0.873
GARCH	3.122	9.748	2.192	-0.135
LSTM	1.422	2.023	1.148	0.757

TABLE IX. Evaluation of Max Temperature, Region: Mymensingh

Variable	RMSE	MSE	MAE	R^2
ARIMA	6.067	36.813	4.559	-0.42
SARIMA	0.835	0.698	0.669	0.973
GARCH	5.569	31.018	4.377	-0.196
LSTM	1.278	1.635	0.942	0.936

TABLE X. Evaluation of Max Temperature, Region: Mymensingh

Variable	RMSE	MSE	MAE	R^2
ARIMA	2.672	7.14	2.281	-0.018
SARIMA	0.986	0.972	0.766	0.861
GARCH	2.672	7.14	2.082	-0.018
LSTM	1.404	1.973	1.151	0.708

TABLE XI. Evaluation of Max Temperature, Region: Shylet

Variable	RMSE	MSE	MAE	R^2
ARIMA	4.919	24.2	4.364	-0.001
SARIMA	0.723	0.523	0.524	0.978
GARCH	5.355	28.676	4.226	-0.186
LSTM	1.444	2.087	1.127	0.912

TABLE XII. Evaluation of Min Temperature, Region: Shylet

Variable	RMSE	MSE	MAE	R^2
ARIMA	3.958	15.673	2.658	-0.322
SARIMA	1.17	1.37	0.955	0.884
GARCH	3.728	13.899	2.577	-0.172
LSTM	1.82	3.3127	1.407	0.714

TABLE XIII. Evaluation of Max Temperature, Region: Rangpur

Variable	RMSE	MSE	MAE	R^2
ARIMA	10.155	103.134	8.462	-2.372
SARIMA	0.722	0.521	0.575	0.982
GARCH	5.924	35.103	4.768	-0.147
LSTM	1.291	1.666	1.08	0.944

TABLE XIV. Evaluation of Min Temperature, Region: Rangpur

Variable	RMSE	MSE	MAE	R^2
ARIMA	3.458	11.962	2.455	-0.668
SARIMA	0.845	0.713	0.686	0.9
GARCH	2.686	7.217	2.091	-0.007
LSTM	1.533	2.352	1.247	0.663

TABLE XV. Evaluation of Max Temperature, Region: Barishal

Variable	RMSE	MSE	MAE	R^2
ARIMA	5.338	28.503	4.255	-0.094
SARIMA	0.885	0.784	0.641	0.969
GARCH	6.038	36.461	4.244	-0.399

LSTM	1.564	2.446	1.305	0.904

TABLE XVI. Evaluation of Min Temperature, Region: Barishal

B. Performance Comparison

Among the models evaluated, SARIMA delivered good overall performance by effectively capturing the seasonal patterns and trends in temperature data. In contrast, LSTM provided average results, demonstrating reasonable capabilities in handling non-linear relationships but falling short of SARIMA in predictive accuracy. Below is a summary of each model's performance:

a) ARIMA: Produced stable results for non-seasonal patterns but underperformed compared to SARIMA due to its inability to model seasonal components effectively.

b) SARIMA: Achieved strong results, particularly in scenarios with clear seasonal variations, due to its ability to model seasonality through seasonal differencing.

c) LSTM: Delivered average performance, showing potential in modeling non-linear patterns but struggling with the sparse and highly variable nature of temperature data.

d) GARCH: These models were suitable for capturing volatility and heteroscedasticity but were less effective for long-term forecasting due to their limited handling of non-linear and seasonal dynamics.

C. Recommended Model

Among the ARIMA, SARIMA, LSTM, and GARCH models, the best results were obtained using the Seasonal ARIMA (SARIMA) model.

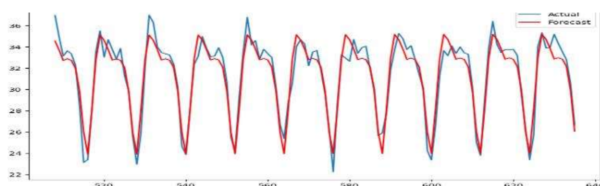

Fig. 1. SARIMA Actual vs Forecast for Max Temperature, Region: Rajshahi

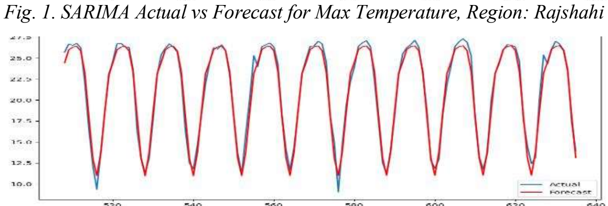

Fig. 2. SARIMA Actual vs Forecast for Min Temperature, Region: Rajshahi

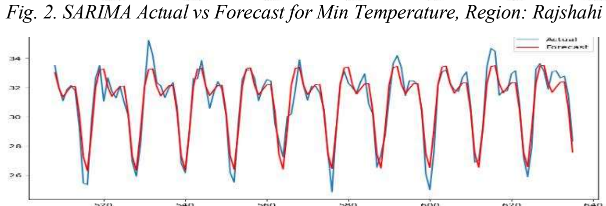

Fig. 3. SARIMA Actual vs Forecast for Max Temp, Region: Chottogram

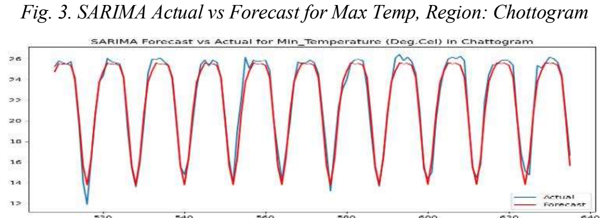

Fig. 4. SARIMA Actual vs Forecast for Min Temp, Region: Chottogram

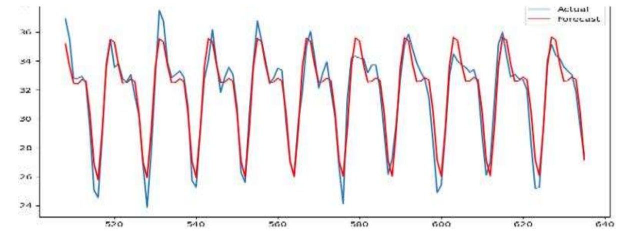

Fig. 5. SARIMA Actual vs Forecast for Max Temperature, Region: Khulna

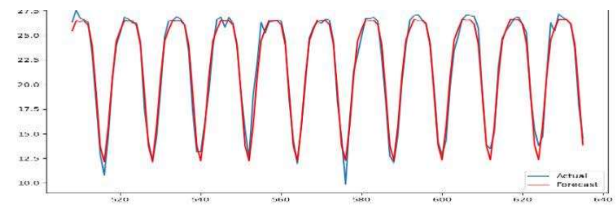

Fig. 6. SARIMA Actual vs Forecast for Min Temperature, Region: Khulna

There are 10 additional figures for the maximum and minimum temperatures of Dhaka, Mymensingh, Barishal, Rangpur, and Sylhet, but they are omitted due to page limitations.

Overall, SARIMA proved to be the most reliable model for temperature forecasting, while LSTM and GARCH models showed potential for specific aspects, such as non-linear dynamics and volatility modeling.

REFERENCES

[1] A. H. Nury, M. Koch, and M. J. B. Alam, "Time series analysis and forecasting of temperatures in the Sylhet division of Bangladesh," in *4th International Conference on Environmental Aspects of Bangladesh (ICEAB)*, August 2013.

[2] A. H. Nury, K. Hasan, M. J. B. Alam, and M. M. Hasan, "Analysis of time series variations of temperature and its forecast in the northeastern Bangladesh," *Int. J. Global Warming*, vol. 13, no. 2, pp. 157-182, 2017.

[3] H. T. Islam, M. Kamruzzaman, S. Shahid, M. Mainuddin, E. Alam, A. R. Islam, J. C. Biswas, and M. A. Islam, "Spatiotemporal changes in temperature projections over Bangladesh using multi-model ensemble data," *Front. Environ. Sci.*, vol. 10, art. 1074974, 2023.

[4] M. Z. Rahman, "Change in temperature over Bangladesh associated with degrees of Global Warming," vol. 2, no. 2, pp. 62–75, 2013.

[5] M. R. Rahman and H. Lateh, "Climate change in Bangladesh: A spatio-temporal analysis and simulation of recent temperature and rainfall data using GIS and time series analysis model," *Theor. Appl. Climatol.*, pp. 1–15, 2015.

[6] N. Sultana and M. M. Hasan, "Forecasting temperature in the Coastal area of Bay of Bengal—an application of Box-Jenkins seasonal ARIMA model," *Statistics*, vol. 7, no. 8, pp. 149-159, 2015.

[7] J. K. Basak, R. A. M. Titumir, and N. C. Dey, "Climate change in Bangladesh: A historical analysis of temperature and rainfall data," *J. Environ.*, vol. 2, no. 2, pp. 41–46, 2013.

[8] M. Hashizume, Y. Wagatsuma, T. Hayashi, S. K. Saha, K. Streatfield, and M. Yunus, "The effect of temperature on mortality in rural Bangladesh—a population-based time-series study," *Int. J. Epidemiol.*, vol. 38, no. 6, pp. 1689–1697, 2009.

[9] J. Zutt, "Warming climate to hit Bangladesh hard with sea level rise, more floods, and cyclones, World Bank Report Says," 2013, pp. 6–8.

[10] S. Shahid, "Probable impacts of climate change on public health in Bangladesh," *Asia Pac. J. Public Health*, vol. 22, no. 3, pp. 310–319, 2010.