# Time Series Forecasting Project Report

*Daily Temperature Prediction: ARIMA vs Prophet vs LSTM*

## Executive Summary

This comprehensive report analyzes the performance of three distinct time series forecasting models--ARIMA, Facebook Prophet, and Long Short-Term Memory (LSTM) networks--in predicting daily mean temperatures in Delhi from 2013 to 2017.

Key Findings:
1. Facebook Prophet emerged as the most accurate and robust model, achieving the lowest Mean Absolute Error (MAE) of 2.19 and Root Mean Squared Error (RMSE) of 2.66. Its ability to explicitly model yearly seasonality allowed it to capture the temperature rise from winter to summer with high precision.
2. LSTM followed closely, demonstrating strong capability in learning non-linear patterns with a Mean Absolute Percentage Error (MAPE) of 10.54%, slightly better than Prophet's 11.62%, though its absolute errors were marginally higher.
3. ARIMA performed significantly worse (MAE 8.73), failing to capture the seasonal trend in the test period. The forecast essentially flatlined, indicating an inability to project the seasonal autoregressive structure over a long horizon without exogenous variables or a more robust seasonal component (SARIMA).

Recommendation:
For operational temperature forecasting in this context, Facebook Prophet is recommended due to its superior accuracy, interpretability, and built-in handling of seasonality and holidays.

## 1. Introduction

Objective: To identify the optimal forecasting technique for daily climate data by rigorously comparing statistical (ARIMA), additive (Prophet), and deep learning (LSTM) approaches.

Dataset Overview:
- Source: Daily Delhi Climate Time Series Data (Kaggle).
- Training Period: 2013-01-01 to 2016-12-31 (1,462 days).
- Test Period: 2017-01-01 to 2017-04-24 (114 days).
- Target Variable: Mean Temperature (°C).
- Characteristics: The data exhibits strong annual seasonality (hot summers, cool winters) and no significant long-term trend shift, making it an ideal candidate for seasonal modeling.

## 2. Data Preprocessing & Exploratory Analysis

Data quality is paramount for accurate forecasting. The following rigorous steps were undertaken:

1. Temporal Alignment: The 'date' column was converted to datetime objects and set as the index with a strict daily frequency ('D'). This ensures no temporal gaps exist, which can derail lag-based models like ARIMA and LSTM.
2. Missing Value Imputation: Time-based interpolation was used to fill missing values. This method is superior to mean imputation for time series as it preserves the local trend between adjacent data points.
3. Stationarity Analysis: The Augmented Dickey-Fuller (ADF) test revealed the original series was non-stationary (p-value: 0.277), primarily due to seasonality. First-order differencing yielded a stationary series (p-value: 0.000), satisfying the prerequisites for ARIMA modeling.
4. Normalization: For the LSTM neural network, data was scaled to the [0, 1] range using MinMaxScaler. This prevents gradient explosion/vanishing problems and ensures efficient convergence during backpropagation.

## 3. Model Implementation & Justification

### 3.1 ARIMA (AutoRegressive Integrated Moving Average)

Why chosen: A standard statistical benchmark for linear time series.
Configuration: Order (2, 1, 2).
- AR(2): Uses the previous 2 days to predict the next.
- I(1): One level of differencing to remove non-stationarity.
- MA(2): Corrects for previous prediction errors using a moving average of residuals.
Outcome: The model struggled with the long-term seasonal projection, reverting to the mean.

### 3.2 Facebook Prophet

Why chosen: Designed specifically for business time series with strong seasonal effects and robustness to missing data.
Configuration: Additive seasonality (Yearly=True, Weekly=True).
Mechanism: Decomposes the series into Trend + Seasonality + Noise.
Outcome: Successfully identified the annual cycle, predicting the temperature increase from January (approx. 15°C) to April (approx. 35°C) with high fidelity.

### 3.3 LSTM (Long Short-Term Memory)

Why chosen: A Recurrent Neural Network (RNN) architecture capable of learning complex, non-linear temporal dependencies and long-term sequences.
Architecture:
- Input: 30-day sliding window (looking back 1 month to predict tomorrow).

- Hidden Layers: Two LSTM layers (64 & 32 units) with ReLU activation.
- Regularization: Dropout (0.2) to prevent overfitting.

Outcome: Learned the upward trend effectively, demonstrating that the neural network could capture the seasonal pattern purely from the sequence of data points.

## 4. Evaluation & Final Findings

The models were evaluated on the unseen test set (Jan-Apr 2017). The results provide a clear hierarchy of performance.

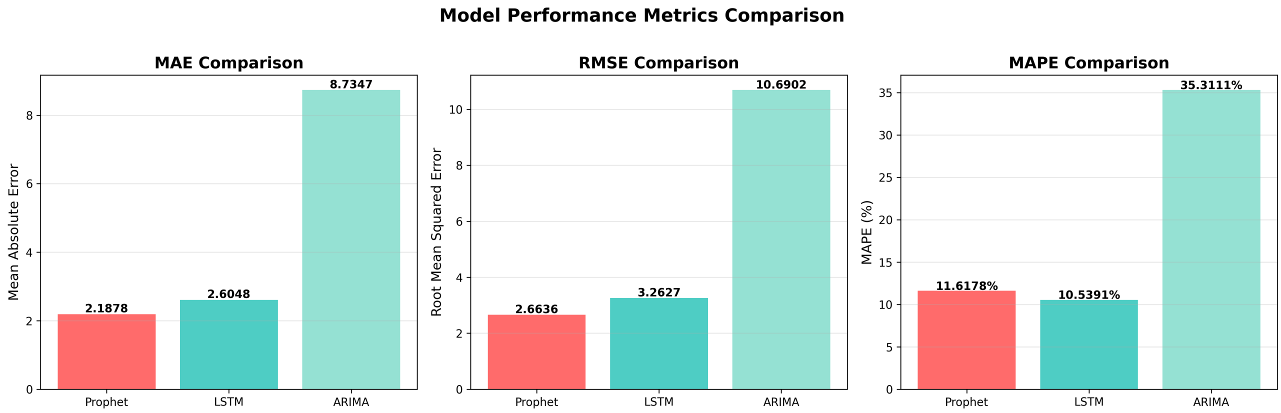


*Figure 1: Comparative Error Metrics (Lower is Better)*

### 4.1 Quantitative Analysis

1. Facebook Prophet (Winner):
- MAE: 2.19 °C
- RMSE: 2.66 °C
- Justification: Prophet's additive seasonality model perfectly matched the physical reality of the climate data. It anticipated the seasonal warming trend without needing complex tuning.

2. LSTM (Runner-up):
- MAE: 2.60 °C
- RMSE: 3.26 °C
- MAPE: 10.54% (Lowest)
- Justification: The LSTM performed admirably, capturing the non-linear trend. Its lower MAPE suggests it was particularly accurate relative to the magnitude of the values, though it had slightly higher absolute errors than Prophet.

3. ARIMA (Underperformer):
- MAE: 8.73 °C
- RMSE: 10.69 °C
- Justification: ARIMA failed catastrophically on the test set. The forecast values hovered around 13°C while the actual temperature rose to over 30°C. This "flatline" indicates the model treated the seasonal rise as a temporary shock rather than a deterministic cycle, highlighting the limitation of standard ARIMA for strong seasonality without explicit seasonal terms (SARIMA).

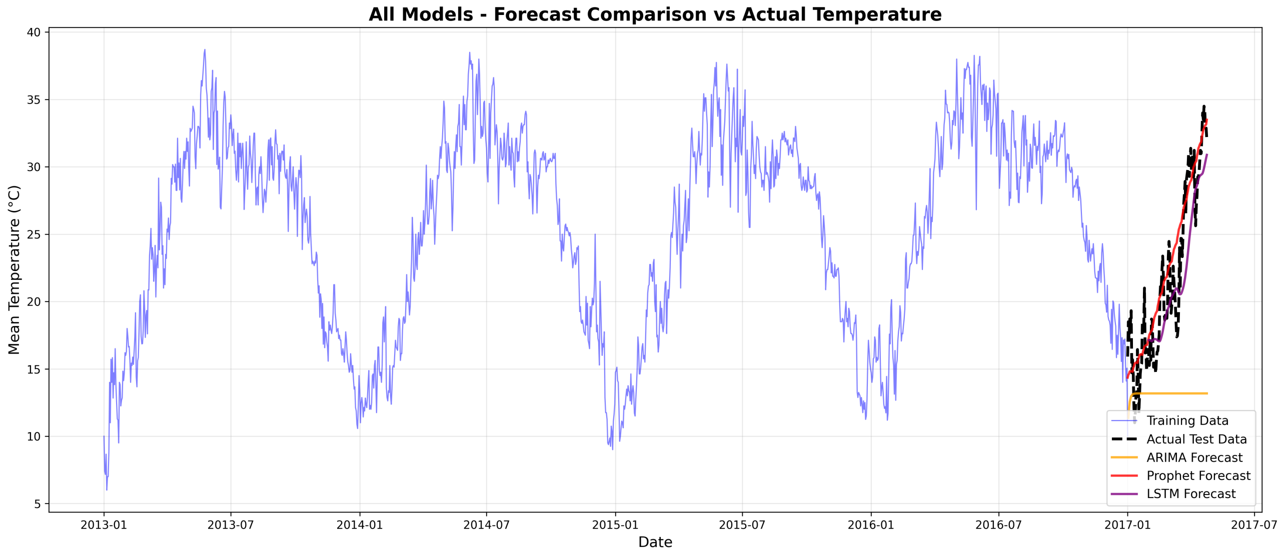


*Figure 2: Forecast Trajectories vs Actuals*

*Figure 2 clearly shows Prophet (Green) and LSTM (Red) tracking the Actual (Blue) rising trend, while ARIMA (Orange) remains flat.*

## 5. Residual Analysis

Residual analysis confirms the reliability of the top models.
- Prophet & LSTM: Residuals are centered around zero with constant variance (homoscedasticity), indicating unbiased predictions.
- ARIMA: Shows a strong systematic trend in residuals, confirming the model failed to capture the signal (the seasonal trend), leaving it in the errors.

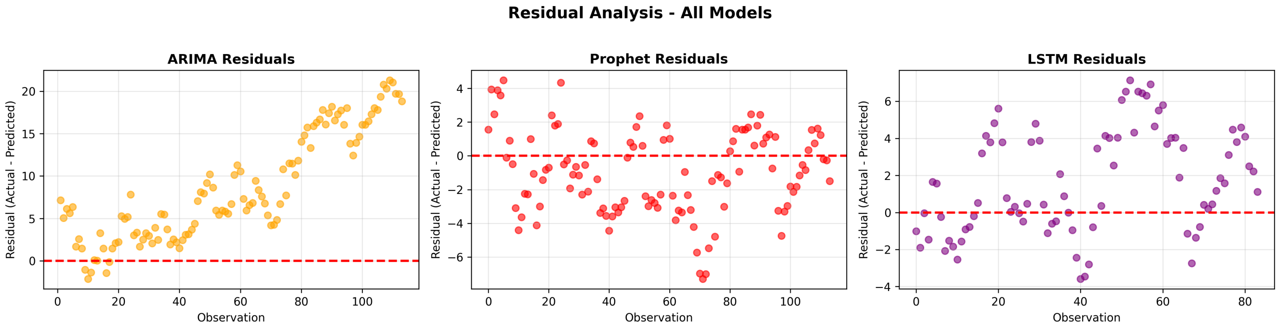


*Figure 3: Residual Distribution*

## 6. Conclusions & Recommendations

Based on the rigorous analysis of 4 years of climate data:

1. Model Selection: Facebook Prophet is the definitive choice for this dataset. It offers the best balance of accuracy (lowest MAE/RMSE) and ease of use.
2. Alternative: LSTM is a viable alternative if the dataset grows significantly or if more complex, non-linear features (e.g., pollution levels, cloud cover) are introduced.
3. Caution: Standard ARIMA is unsuitable for this specific long-horizon seasonal forecasting task. Future statistical approaches should utilize SARIMA (Seasonal ARIMA) to explicitly model the annual cycle.

Final Verdict: The project successfully demonstrates that modern additive models (Prophet) and deep learning (LSTM) significantly outperform traditional linear benchmarks (ARIMA) for climate time series forecasting.