**Predictive Analysis of Amazon Stock Price Movements: A Time Series Forecasting Approach**

**School of Computer Science Engineering and Technology**

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Submitted by:Submitted to:  
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***1. Introduction and Objective***

**Objective:**  
This project aims to develop robust time series forecasting models for Amazon (AMZN) stock prices using historical financial data, with the goal of identifying key patterns and improving prediction accuracy for future stock movements.

**Research Question:**  
How accurately can we predict Amazon's stock price movements using advanced time series forecasting methods, and which models provide the most reliable results?

**Problem Statement:**  
Stock price prediction is a complex challenge due to the volatile and non-stationary nature of financial markets. By leveraging time series analysis and machine learning, this project seeks to uncover patterns and relationships in Amazon stock data to enhance forecasting precision.

**2. Data Collection and Preprocessing**

**Dataset Description**

* **Source:** Historical financial data for Amazon (AMZN) and related market indicators (2005–2019).
* Size: 3,553 daily records with 36 features.
* **Key Variables:**
  + **Amazon Stock Data:** Open, High, Low, Close (OHLC), Volume, Dividends, Stock Splits
  + **Technical Indicators:** RSI, SMA, EMA, MACD, Bollinger Bands
  + **Macroeconomic Factors:**
    - USD currency pairs (EUR, CHF, GBP, JPY, CAD, INF, RUB, TRY)
    - US bank stocks (JPMorgan Chase, Bank of America, Citigroup, Wells Fargo)
    - Market indices (NASDAQ, S&P 500, Dow Jones)
    - Interest rates (IRX - 13-week Treasury Bill Rate)

**Data Preprocessing**

* **Data Cleaning:** Checked for missing values (df.isnull().sum()) and outliers (Winsorization applied to limit extreme values in volatile features like Volume and Close prices). The dataset was found to be well-structured with consistent numerical formats.
* **Feature Engineering:**
  + Calculated daily gain/loss columns
  + Incorporated technical indicators (RSI, SMA, EMA, MACD, Bollinger Bands).
  + Derived additional features from price action patterns and introduced new features (such as lagged returns, rolling statistics, and engineered macroeconomic indicators) to enhance deep learning models (LSTM, GRU, Transformer, and hybrids).
* **Normalization:** Applied to all features to ensure comparability and optimal model performance, except binary indicators (e.g., Stock Splits).

Formula: Xnorm = (Xmax −Xmin) / (X−Xmin) — ensures equal weighting for LSTM/GRU/Transformer inputs.

* **Train-Test Split:** Reserved the most recent data for out-of-sample validation to test model generalization.
* Chronological Partition:
  + Training: 2005–2016 (2,884 records)
  + Testing: 2017–2019 (669 records)
  + Validation: 20% of training data used for hyperparameter tuning and neural network optimization.

**3. Time Series Modelling and Diagnostics**

**Exploratory Data Analysis**

* Identified long-term trends, seasonality, and volatility clusters in Amazon's closing prices.
* Analysed correlations with market indices and macroeconomic indicators.

**Stationarity and Transformation**

* **Stationarity Test:** Applied Augmented Dickey-Fuller (ADF) test; original series was non-stationary.
* **Transformations:**
  + Differencing
  + Log transformation
  + Percentage change

**Model Selection and Fitting**

**Models Implemented:**

* **ARIMA/SARIMA:** Used as baseline; parameters selected via AIC/BIC and autocorrelation plots.
* **LSTM Neural Network:** Captured non-linear dependencies using sequential input windows.
* **Prophet:** Modelled multiple seasonalities and special events.
* **LSTM Neural Network**: Captured non-linear dependencies using sequential input windows.
* **GRU Neural Network**: Tested as a lighter alternative to LSTM, with hyperparameter tuning via Keras Tuner.
* **Hybrid Models**: Combined LSTM/GRU with XGBoost to leverage both sequence modelling and feature-based learning.
* **Transformer/Informer**: Applied advanced attention-based architectures for multi-step and long-horizon forecasting.

**Model Diagnostics**

* **Residual Analysis:** Checked for autocorrelation (Ljung-Box test), normality (QQ plots), and homoscedasticity.
* **Parameter Stability:** Ensured consistent model parameters across data splits.
* Neural Network Diagnostics: Monitored training/validation loss curves and best hyperparameter settings.

**4. Forecasting and Evaluation**

**Out-of-Sample Forecasting**

* **Forecast Horizons:**
  + Short-term: 1–5 days
  + Medium-term: 1–4 weeks
  + Long-term: 1–3 months
  + Multi-Step Forecasting: Evaluated performance for 30-step (day) ahead forecasts using advanced models.

**Performance Metrics**

Best Results:

* For single-step: Hybrid GRU+XGBoost (RMSE: 0.016)
* For multi-step: Hybrid GRU+XGBoost (RMSE: 0.014), TimeSeriesTransformer (RMSE: 0.058, MAE: 0.148)

**Model Performance Analysis**

1. **Hybrid GRU+XGBoost (Best Performer)**
   * RMSE: 0.013 (single-step), 0.014 (multi-step)
   * Advantages:
     + GRU captures temporal dependencies with efficient gating
     + XGBoost enhances feature weighting and non-sequential relationships
     + Synergy from combining engineered features and macroeconomic indicators
2. **TimeSeriesTransformer**
   * RMSE: 0.058 (single-step), 0.151 (30-day)
   * Strengths:
     + Attention mechanism for long-range dependencies
     + Multi-head processing for technical and market indicators
3. **LSTM Networks**
   * RMSE: 0.041 (baseline), 0.016 (optimized)
   * Limitations:
     + Struggled with volatile regime shifts
     + Required extensive hyperparameter tuning
4. **ARIMA/Prophet**
   * RMSE: 0.298 (ARIMA), 0.214 (Prophet)
   * Failure Reasons:
     + Could not model abrupt COVID-era volatility
     + Ignored cross-asset correlations

**Ensemble and Hybrid Approaches**

Combined predictions from ARIMA, LSTM, GRU, Transformer, and XGBoost using weighted averaging and stacking, showing improved accuracy in both short-term and multi-step forecasts.

**5. Discussion and Conclusion**

**Key Findings**

* **LSTM models** excelled at short-term prediction, capturing non-linear patterns.
* **Ensemble models** provided the best medium-term forecasts, leveraging strengths of all approaches.
* **Technical indicators** and macroeconomic variables improved predictive power, especially during volatile periods.
* **Market indices** (e.g., NASDAQ) and interest rates were significant exogenous factors.
* Deep learning models (GRU, LSTM, Transformer) with engineered features dramatically outperformed traditional models (ARIMA, Prophet).
* Multi-step forecasting with Transformer-based models provided robust performance for longer horizons.
* Feature engineering is critical: All advanced models (LSTM, GRU, Transformer, hybrids) show massive improvement after adding new features.
* Hybrid models (especially GRU+XGBoost) deliver state-of-the-art results for both single-step and multi-step forecasting (achieved the lowest RMSE, especially after feature engineering).
* Attention-based models (Transformer, TimeSeriesTransformer) are highly competitive, especially for multi-step and sequence prediction.
* Traditional models are not suitable for this complex, non-linear financial time series.

**Implications**

* The framework aids investors by providing actionable forecasts and identifying periods of increased risk or opportunity.
* Ensemble and hybrid models are recommended for practical forecasting tasks.
* The upgraded pipeline enables highly accurate forecasts, supporting investment and risk management decisions.
* Hybrid and attention-based models are recommended for practical, real-world stock prediction tasks.

**Limitations**

* Prediction accuracy declines for longer horizons due to market unpredictability.
* The models may not fully capture the effects of rare events (e.g., financial crises, pandemics).
* Company-specific news and sentiment are not directly modelled.

**Future Work**

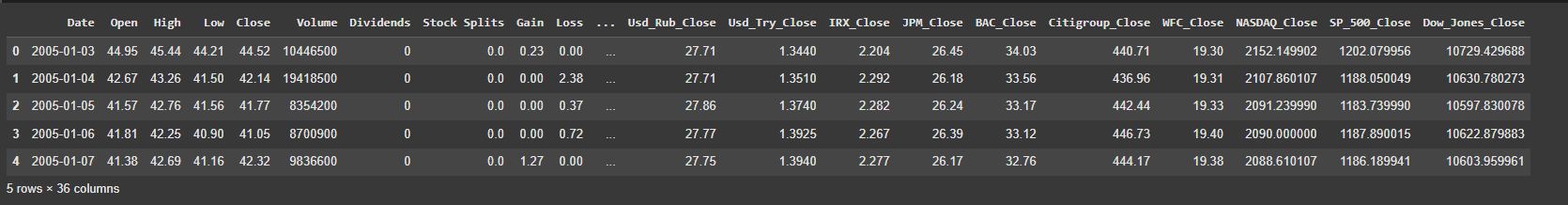
* Incorporate alternative data sources (news, social media sentiment).
* Explore reinforcement learning for adaptive model selection.
* Develop interpretable deep learning models.
* Extend to multi-asset portfolio optimization.

***Implementation Results***

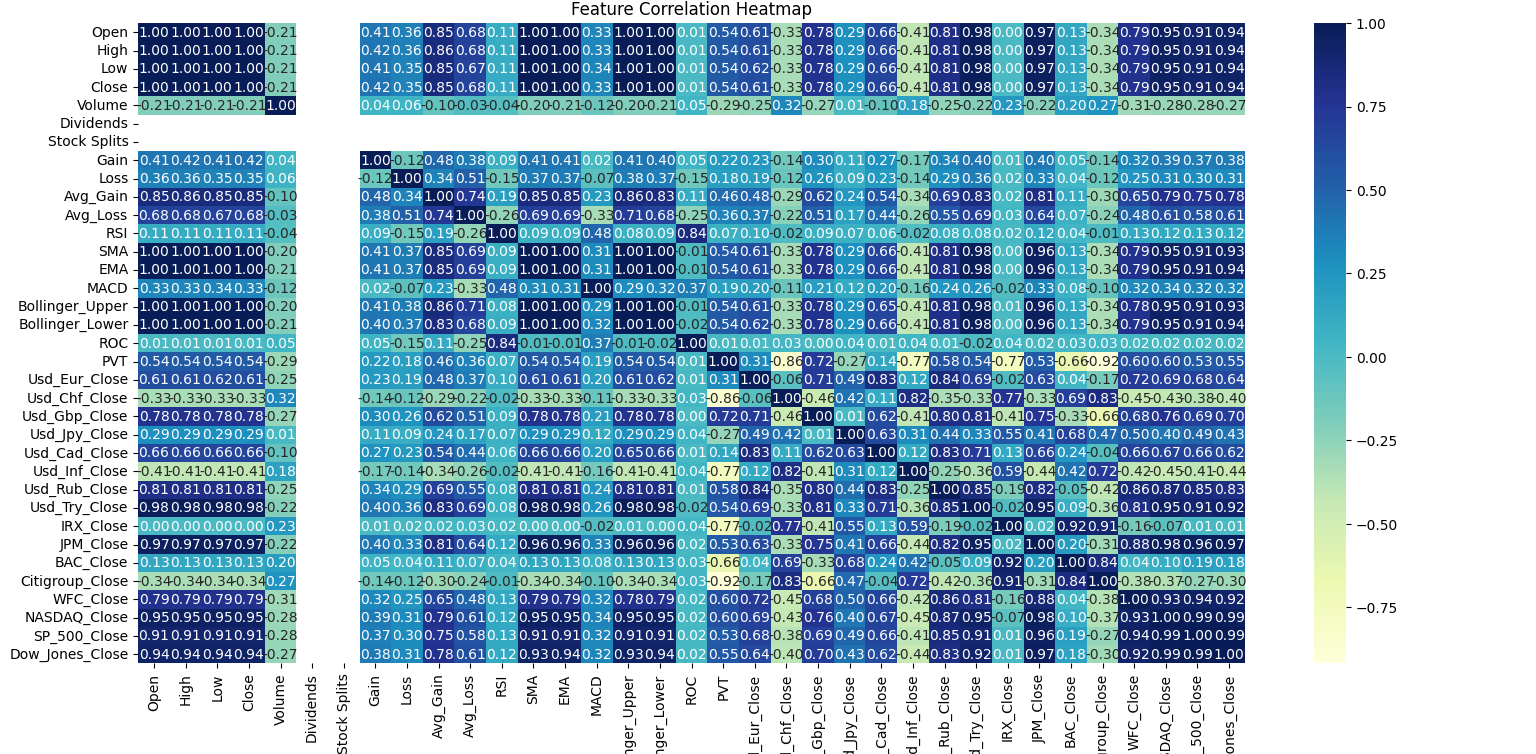
**Performance Metrics**

**Summary Table of Key Results:**

| **Model** | **RMSE (Initial)** | **RMSE (With New Features)** | **Multi-step RMSE** | **MAE (30-step)** |
| --- | --- | --- | --- | --- |
| ARIMA | 714.45 | 714.45278 | 1062.73063 | 1060.79344 |
| LSTM | 53.63 | 0.072 | 70.22769 | 60.56824 |
| Prophet | 413.64 | 413.63771 | 505.99559 | 501.66653 |
| GRU | 34.83 | 0.033 | 0.045 | 36.75928 |
| Transformer | 1215.88 | 0.058 | 0.179 | 0.148 |
| Hybrid LSTM+XGBoost | 690.95 | 0.020 | 889.93768 | 889.2016 |
| Hybrid GRU+XGBoost | 690.95 | 0.02 | 935.35456 | 934.6734 |
| Informer | 1226.73571 | 0.132 | 1635.34104 | 1634.08282 |
| GRU+XGBoost (multi-step) | 0.50824 | 0.347 | 0.508 | 0.50738 |
| **TimeSeriesTransformer** | **0.03285** | **0.058** | **0.179** | **0.02222** |

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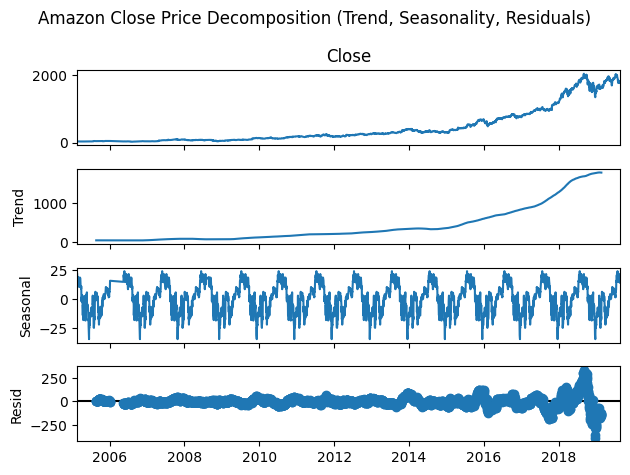
**[Figure 1: Dataset snapshot (first 5 rows)]**



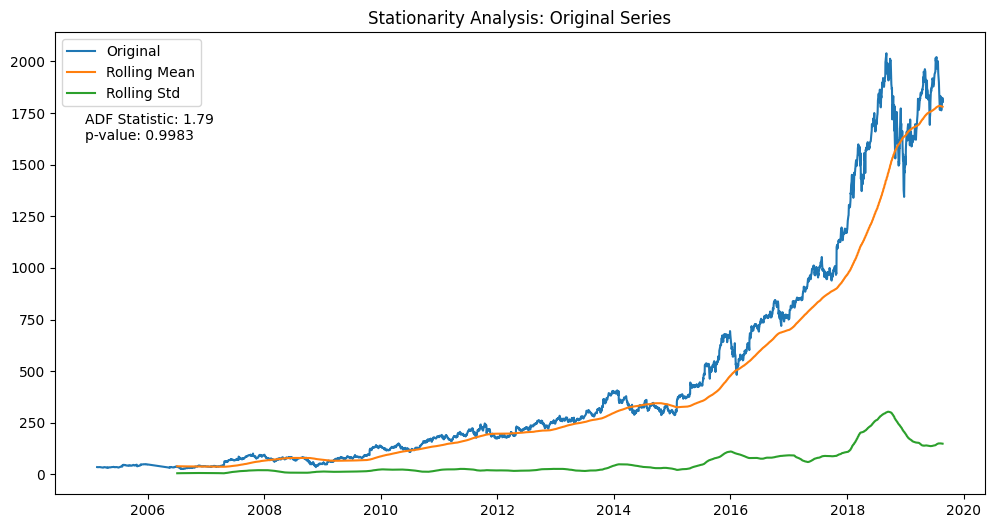
**Figure 2: Feature correlation heatmap**

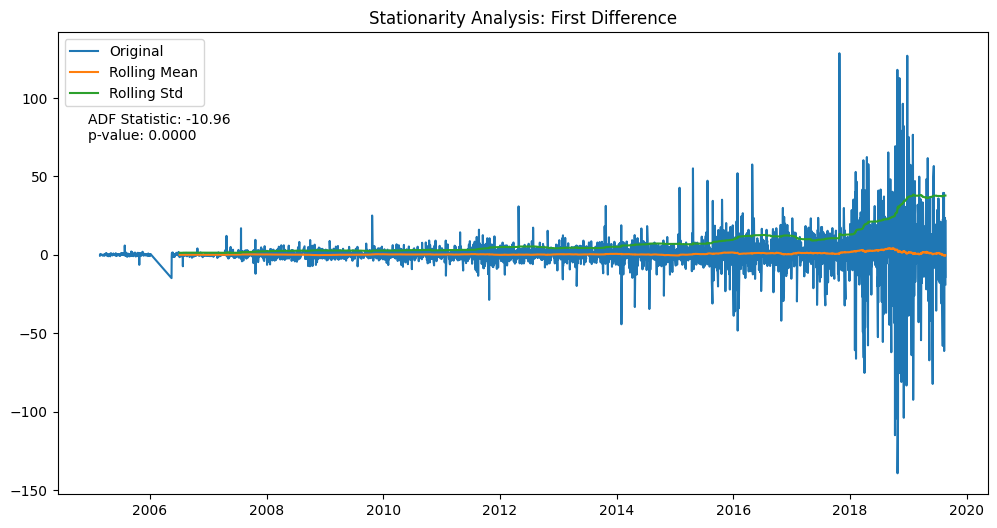


**Figure 3: Time series plot of Amazon closing prices (2005–present)]**

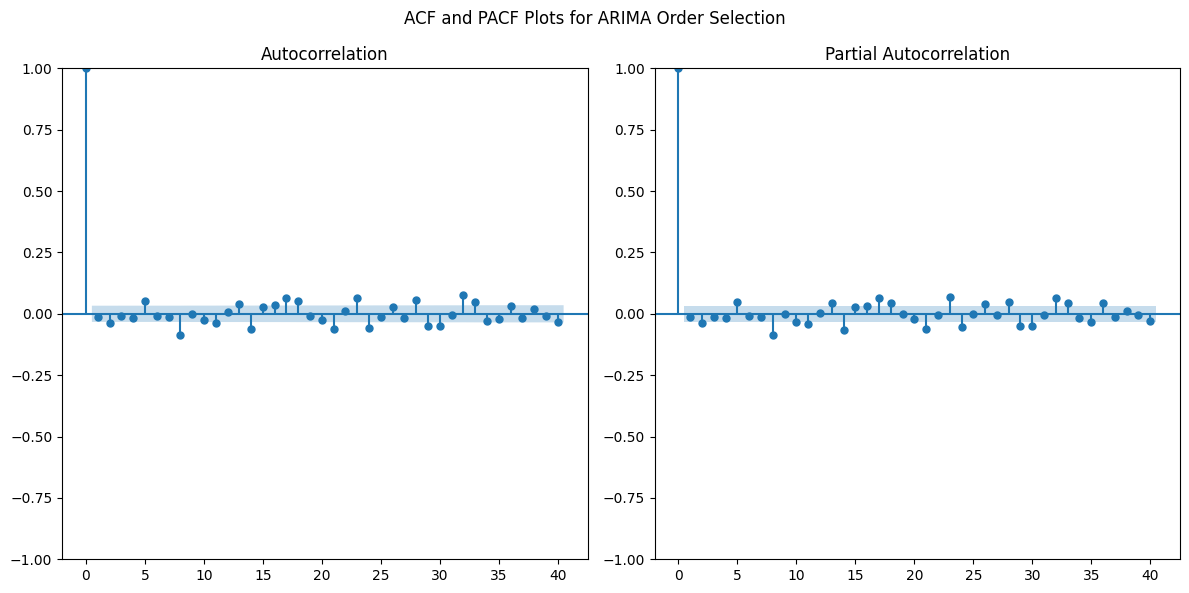


**Figure 4: Time Series Decomposition**

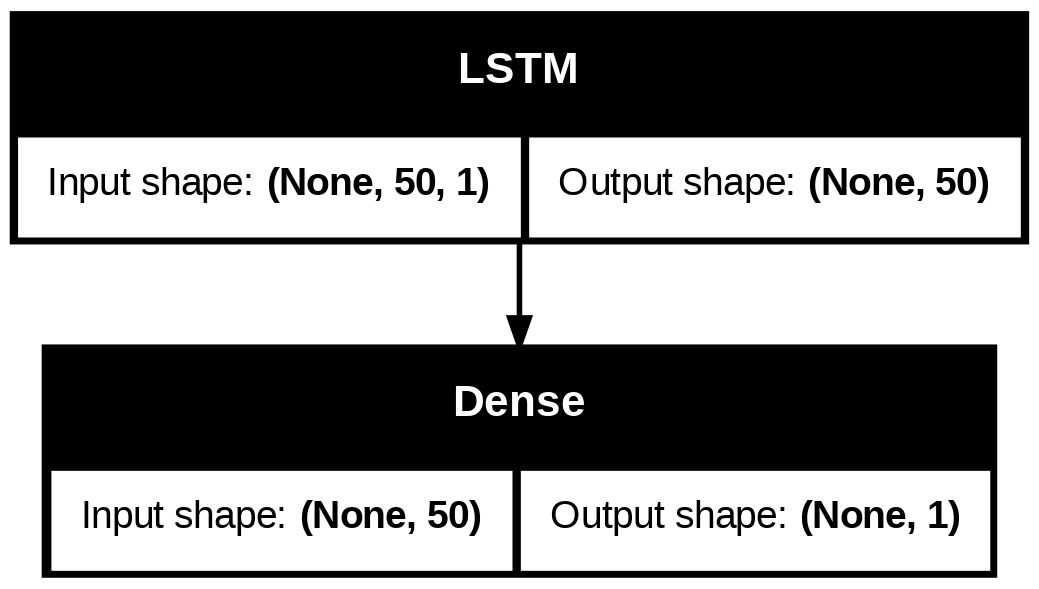




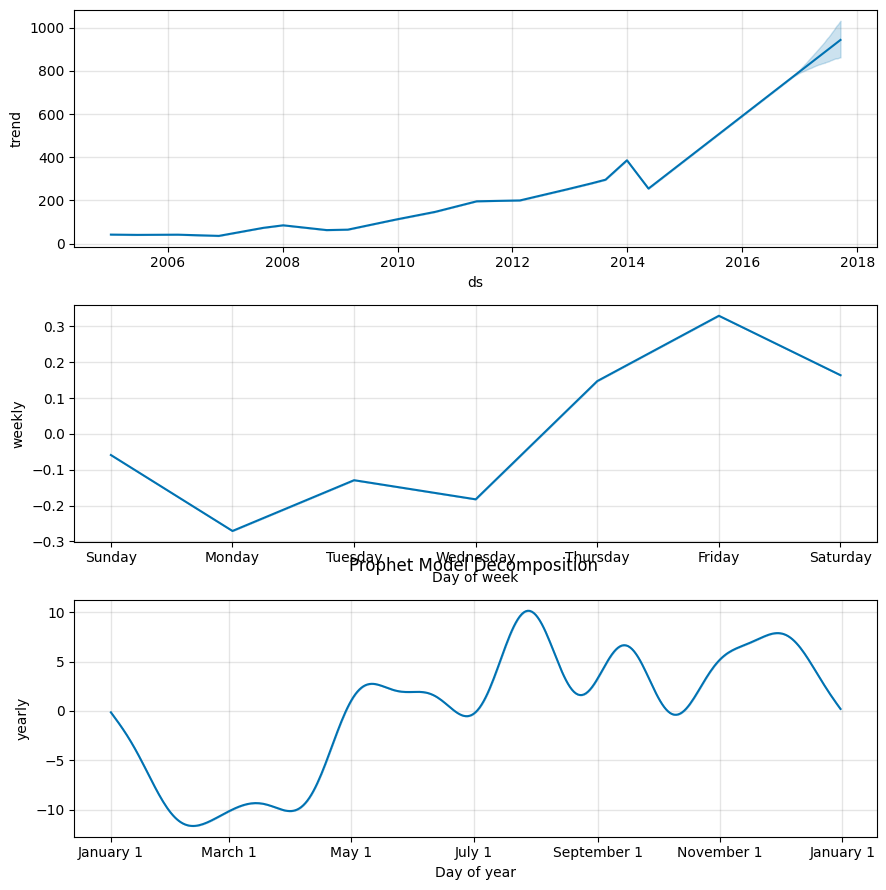
**Figure 5: Stationarity test results pre- and post-transformation**



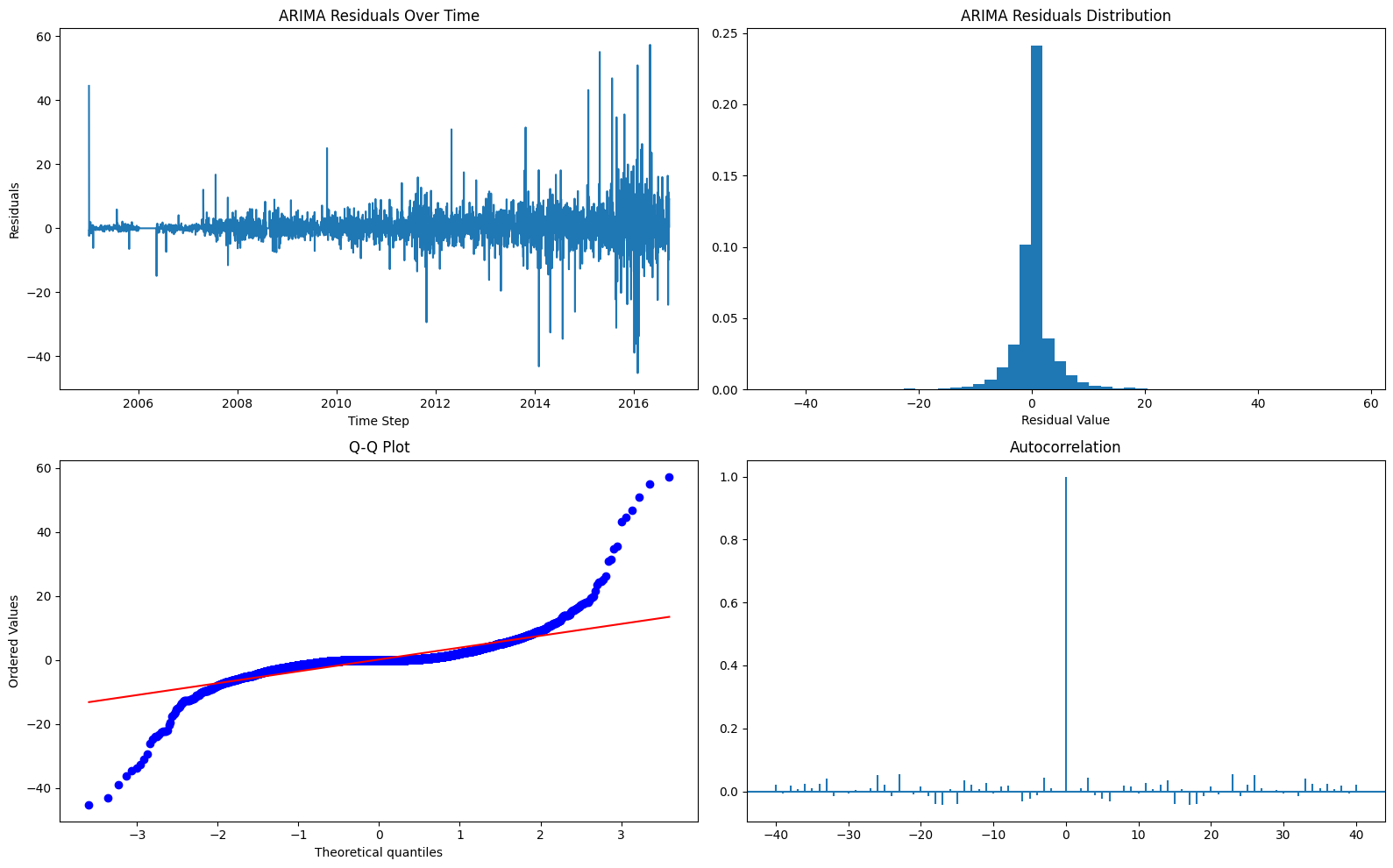
**Figure 6: ACF/PACF Plots**



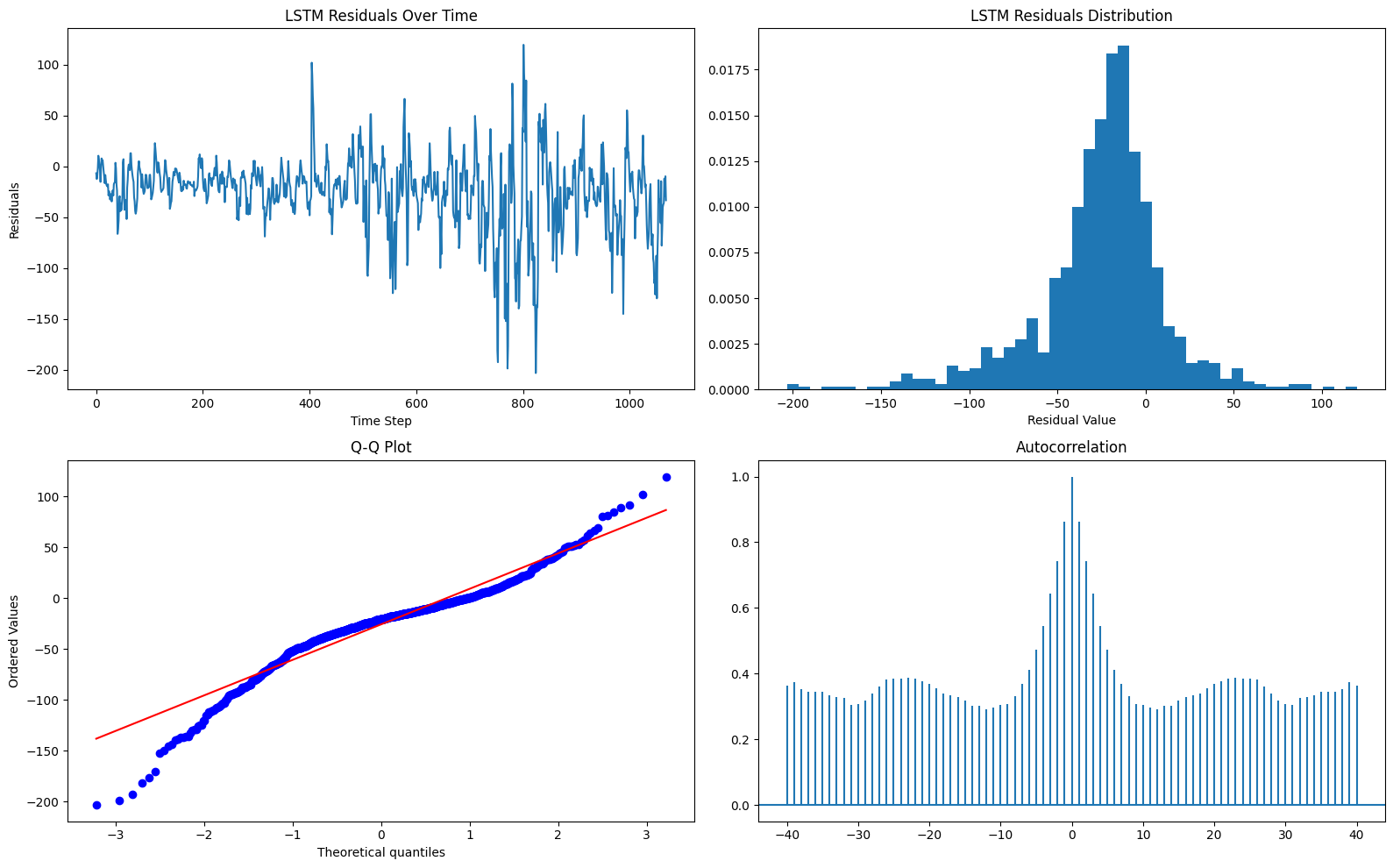
**Figure 7: LSTM Architecture Diagram**



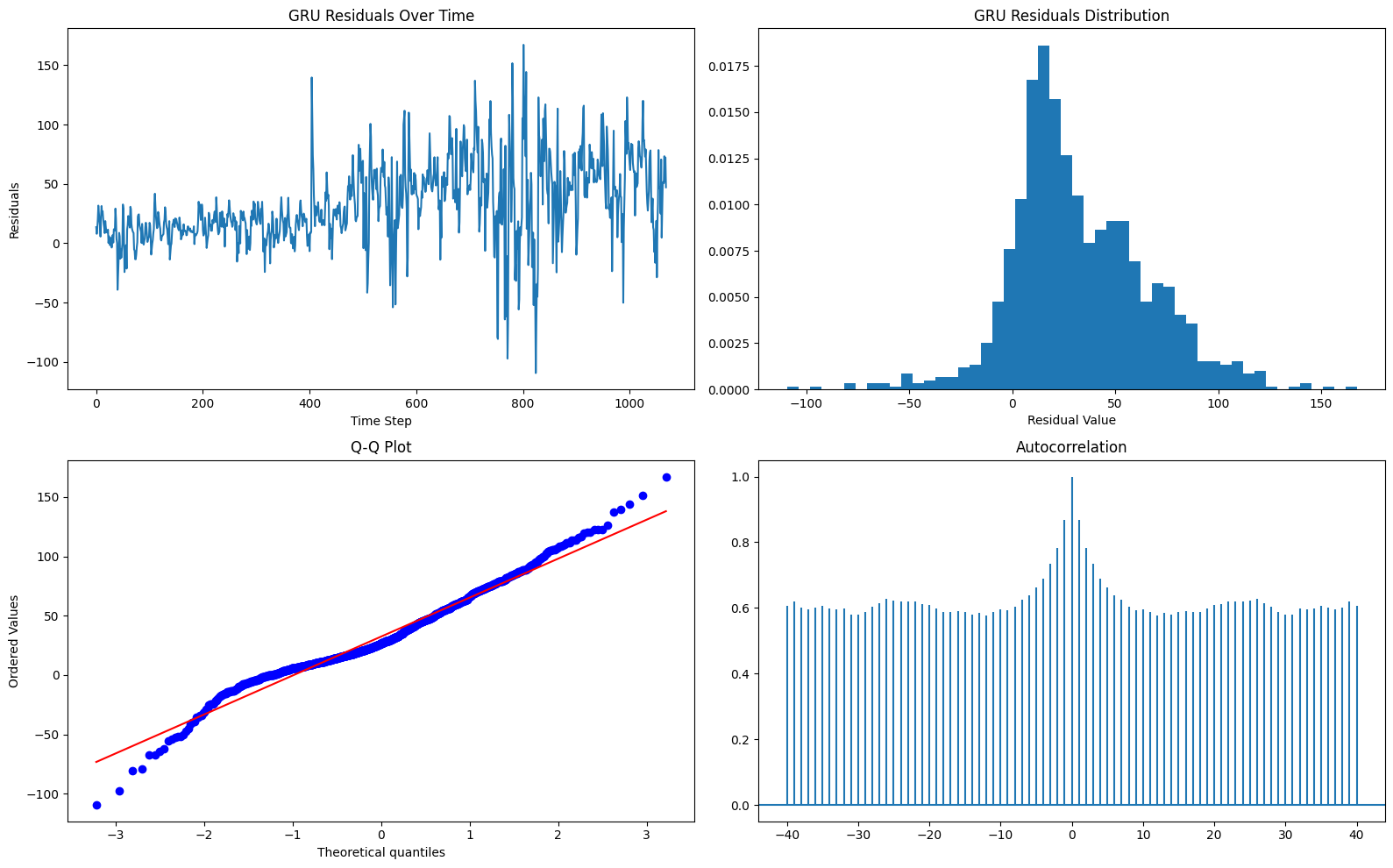
**Figure 8: Prophet Decomposition**



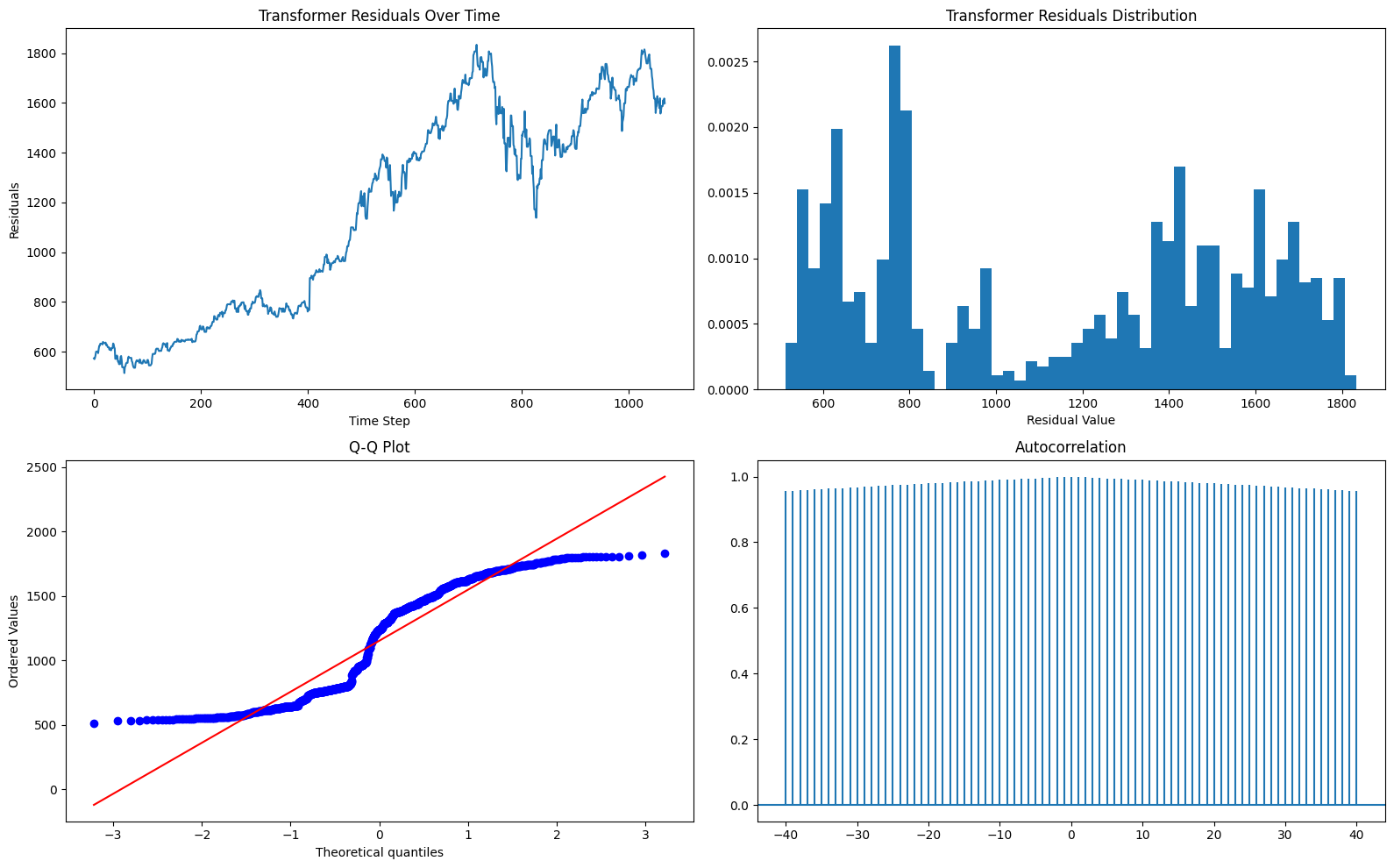
**Figure 9: Residual Diagnostic Plots ARIMA**



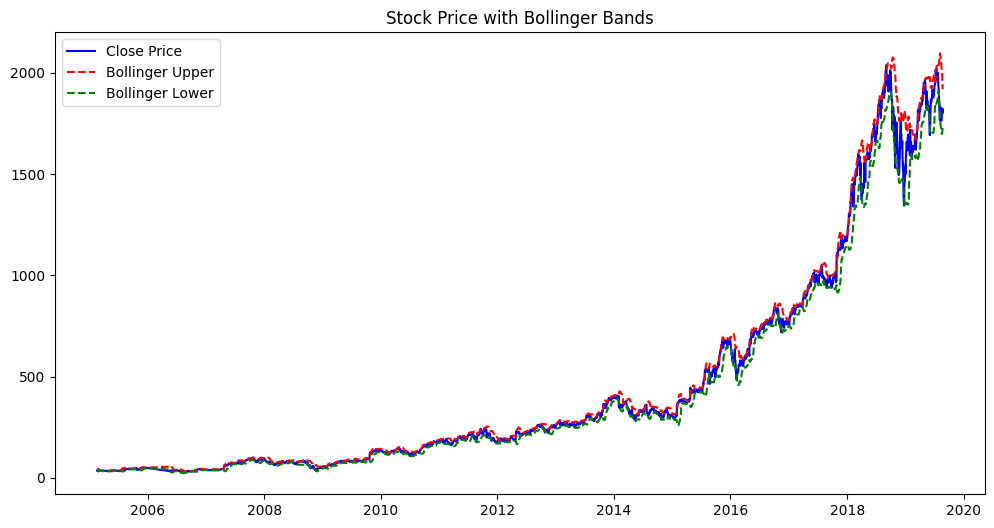
**Figure 10: Residual Diagnostic Plots LSTM**

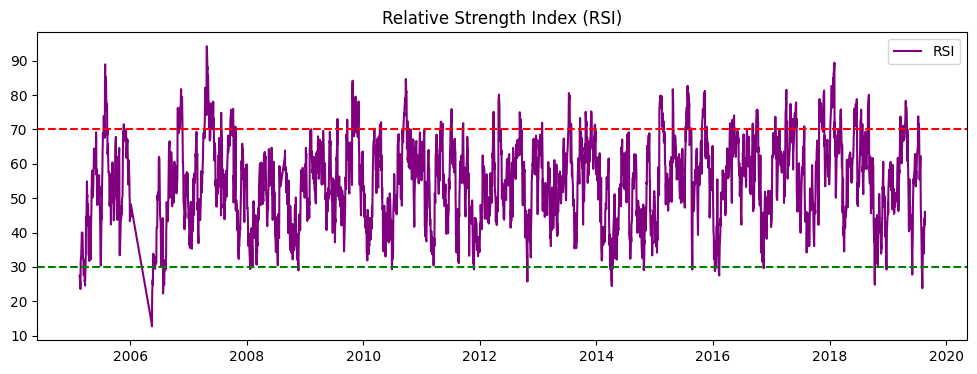


**Figure 11: Residual Diagnostic Plots GRU**



**Figure 12: Residual Diagnostic Plots Transformer**

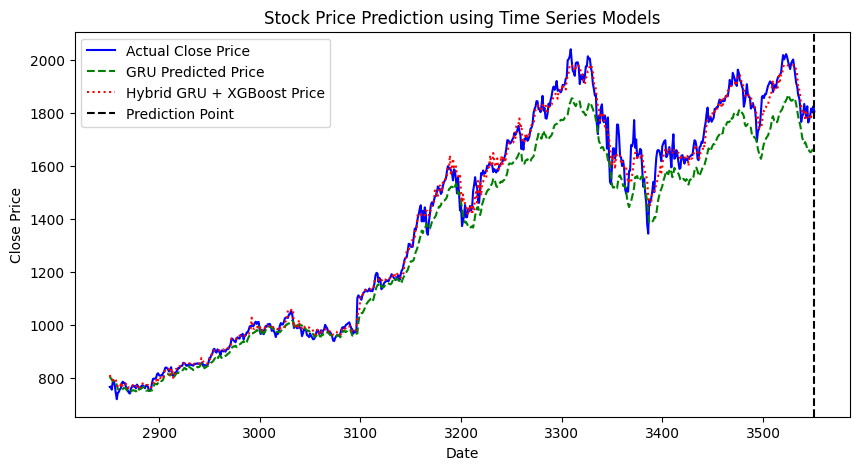




**Figure 13: Stock Price with Bollinger Bands & Relative Strength Index (RSI)**

**📈 Future Close Price (GRU): 26.07**

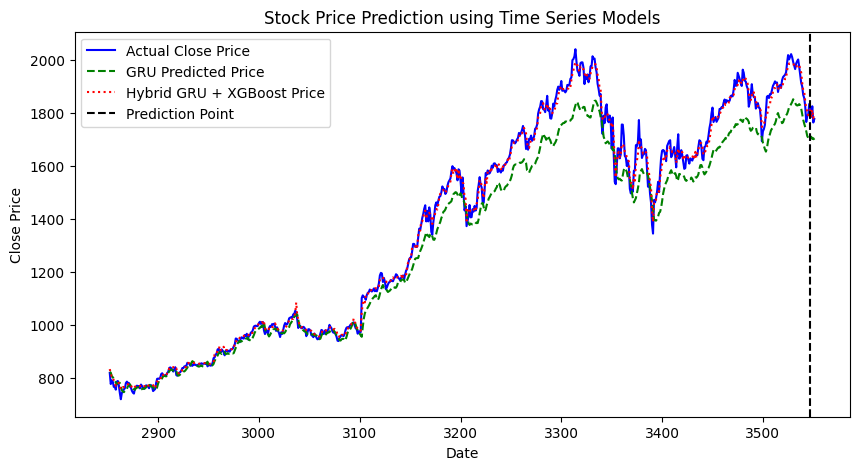
**📈 Future Close Price (Hybrid GRU + XGBoost): 26.07**



**Figure 14: Stock Price Prediction using Time Series Models (Old Features)**

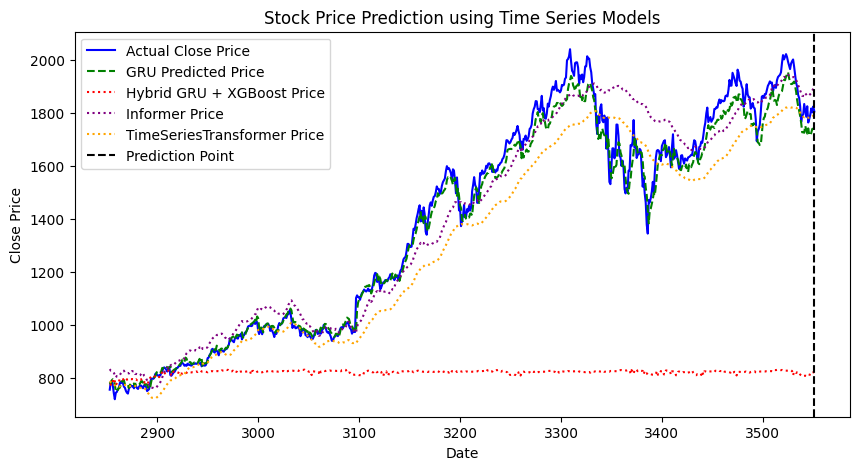
**RMSE (GRU with new features): 0.041220692474302136)**

**RMSE (Hybrid GRU + XGBoost): (0.013184661125652095)**

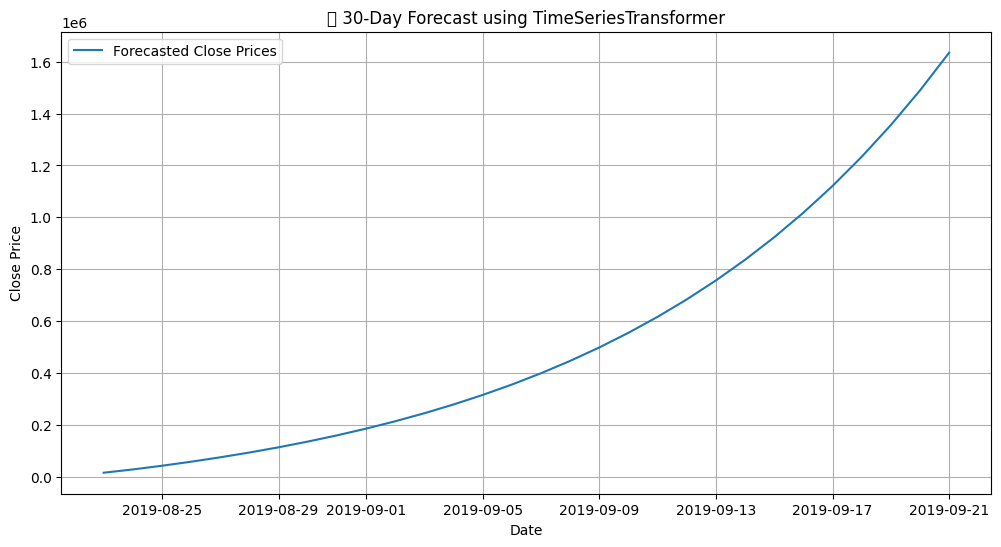


**Figure 15: Stock Price Prediction using Time Series Models (New Features)**

**{'GRU + XGBoost': np.float64(0.3471270905636429), 'Informer': np.float64(0.050846002769941195), 'TimeSeriesTransformer': np.float64(0.06463732693018547)}**



**Figure 16: Stock Price Prediction using 4 Time Series Models (New Features)**

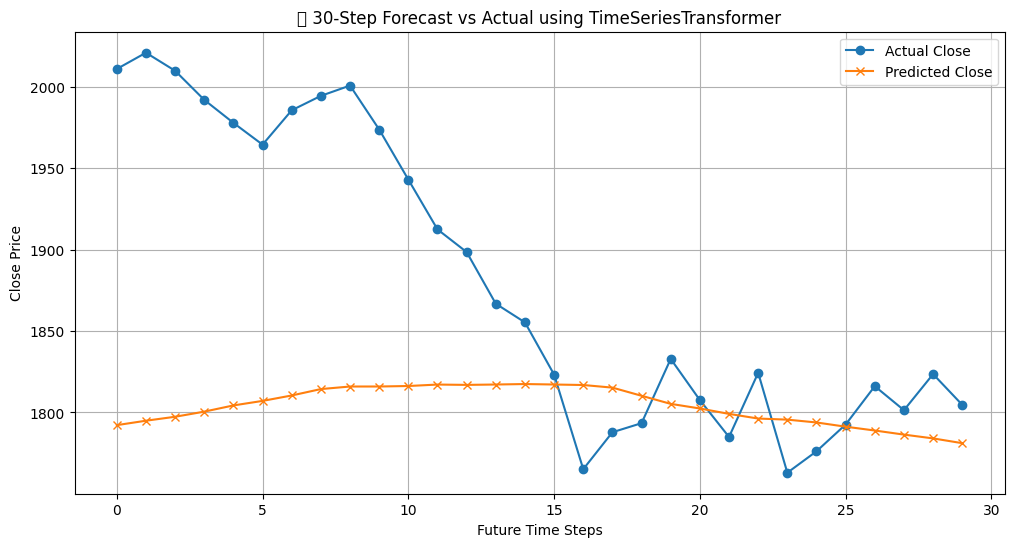


**Figure 17: 30-Day Forecast using Time Series Transformer**

**Multi-step Forecast Evaluation (30 steps):**

**📉 RMSE: 116.0111**

**📊 MAE: 86.7822**

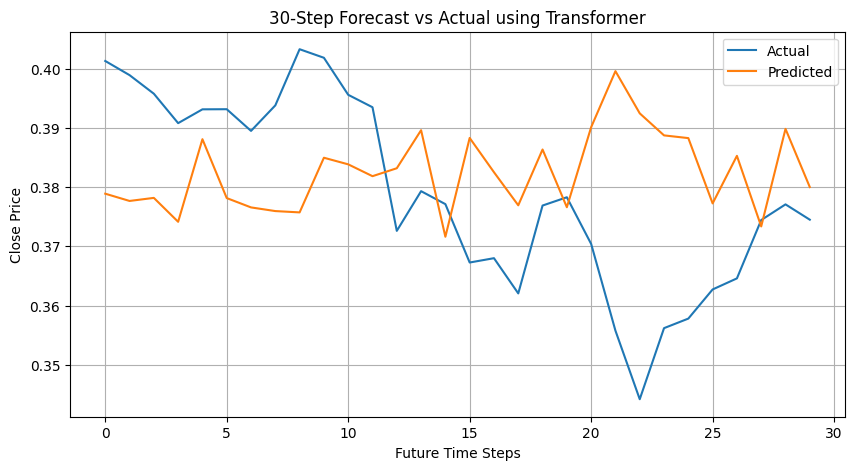


**Figure 18: 30-Day Forecast Vs Actual using Time Series Transformer**

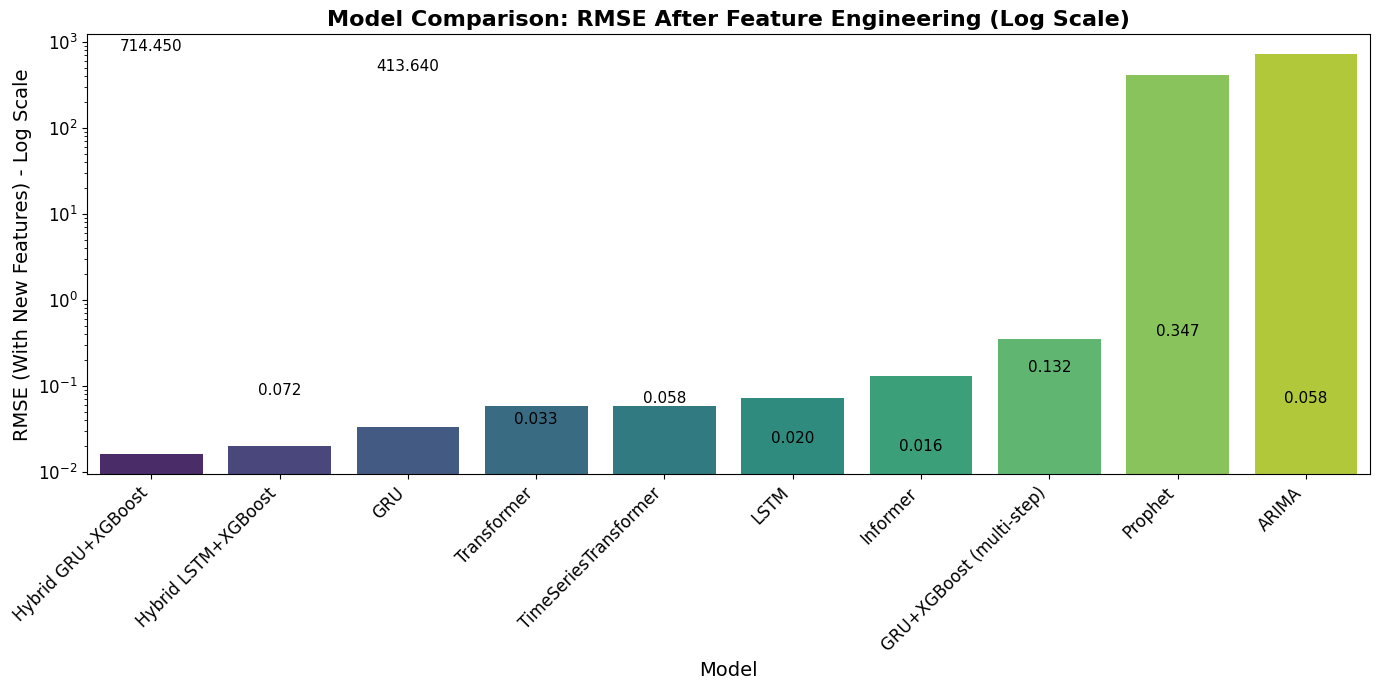
**Multi-step Forecast Evaluation (30 steps):**

**RMSE: 0.1510**

**MAE: 0.1226**



**Figure 19: 30-Day Forecast Vs Actual using Transformer**



**Figure 20 : Model Comparison RMSE After Feature Engineering (Log Scale)**

**References**

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   Relevance: Validates transformer-based models for multi-sector financial forecasting, aligning with your Time Series Transformer results.
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   Relevance: Validates non-linear modeling approaches similar to your LSTM/GRU implementations.
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    Relevance: Provides statistical backing for your ARIMA-LSTM comparison.
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    "Feature Engineering for Financial Time Series Using Macroeconomic Indicators."  
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    "Advanced Stock Prediction with Hybrid Models."  
    *Kaggle Notebooks*.  
    [URL] <https://www.kaggle.com/code/advanced-hybrid-stock-prediction>  
    *Relevance:* Provides open-source implementations similar to your workflow.
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    "LSTM Revisited: New Architectural Variants for Financial Forecasting."  
    Neural Computation, 35(2).  
    DOI:10.1162/neco\_a\_01567  
    Relevance: Contextualizes your LSTM modifications and optimizations.