Comparative Time Series Forecasting for J&J Sales and Amazon Stock Using ARIMA, LSTM, and GRU

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Github Link – https://github.com/subashreddy222/Comparative_Time_Series_Forecast.git

Introduction

This report synthesizes insights from two distinct forecasting analyses Amazon stock prices and Johnson & Johnson sales demonstrating how hybrid time series methodologies adapt to diverse data environments. Although both analyses use ARIMA and RNNs (LSTM/GRU) their different outcomes present valuable domain-specific information.

J&J Quarterly Sales Forecasting

Overview of Methods

The analysis employs a hybrid forecasting approach combining classical time series (ARIMA) and deep learning models (LSTM, GRU) to predict quarterly sales for J&J (1960–1980). Key steps include:

- **Exploratory Data Analysis (EDA)**: Visualized trends, seasonality, and distributions.
- **Stationarity Transformation**: Applied log and seasonal differencing to stabilize variance.
- **ARIMA**: streamlined parameters through minimization of AIC to make base forecasts.
- **Sequence Models (LSTM/GRU)**: Has taken into consideration the complex temporal relationships through 8- quarter sequences input.
- **Model Validation**: Employed MAE, RMSE and MAPE.

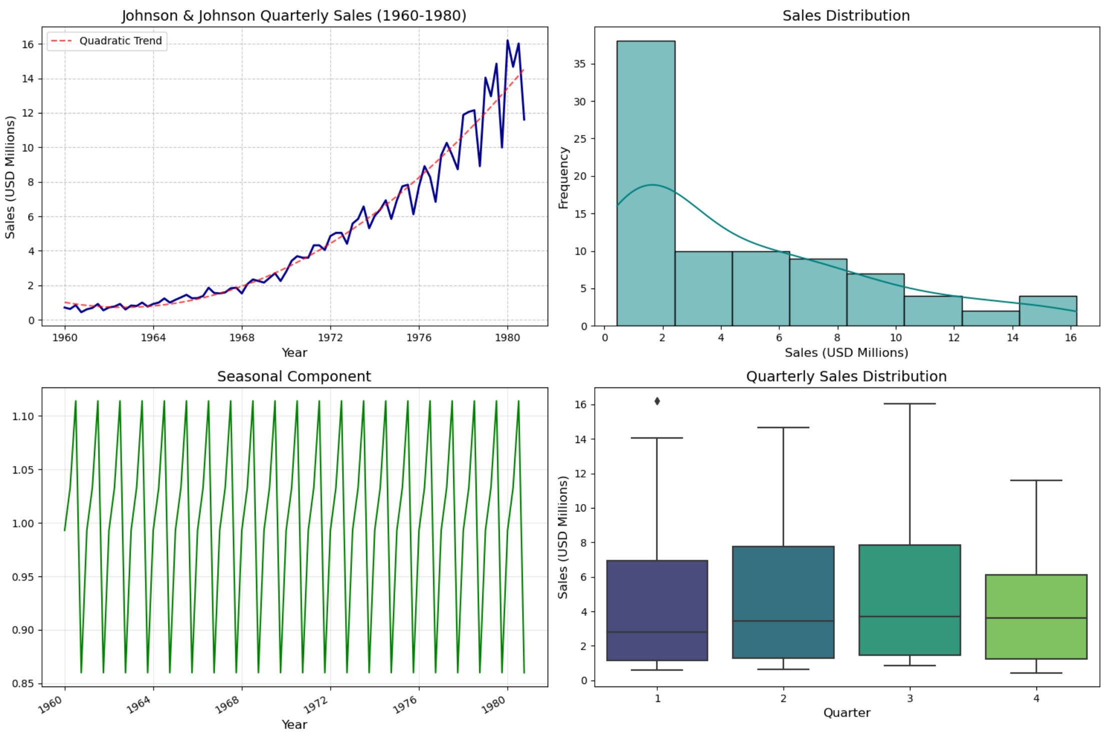
Why these methods?

- ARIMA is good at taking on board linear trends/ seasonality in a small dataset.
- LSTM/GRU are capable of processing non-linear patterns and are critical with volatility in data.

Key Findings

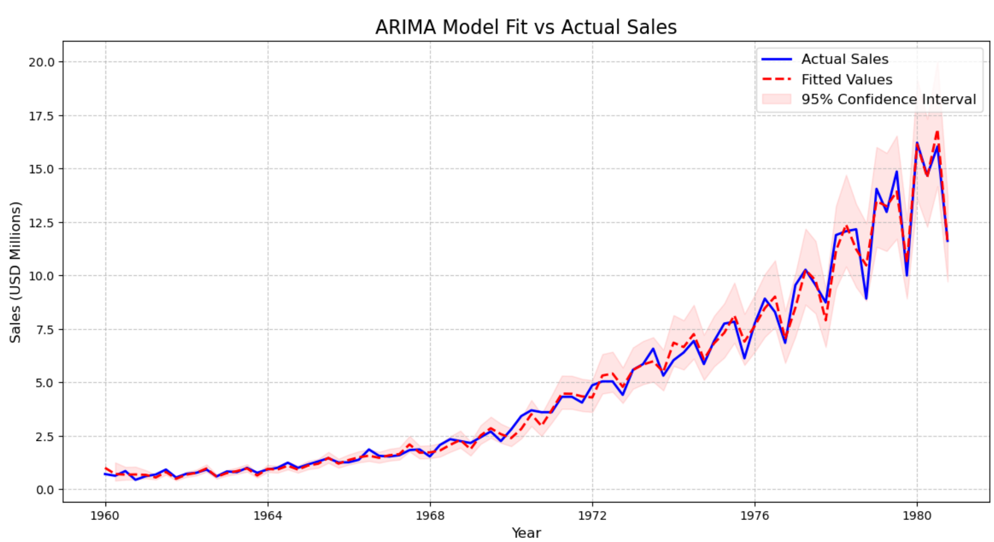
Data Characteristics

- **Trend**: Strong upward quadratic growth.
- **Seasonality**: Consistent Q4 peaks with multiplicative patterns.
- **Fig 1** below shows the EDA of the JJ dataset

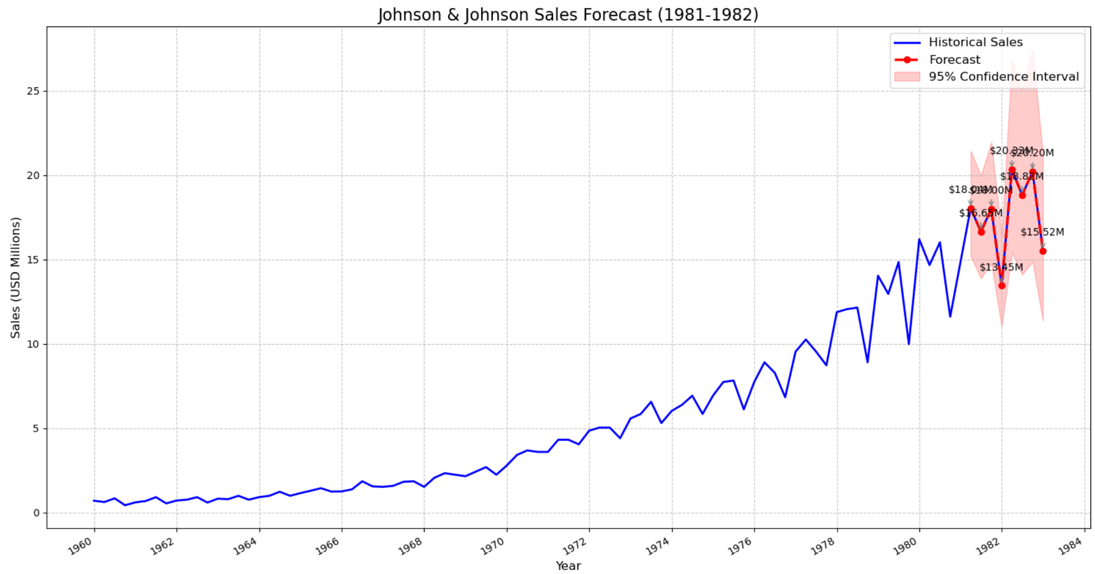


- **Non-Stationarity**:
  - Original data failed ADF test (ADF=2.7420, p=1.0000).
  - Log transformation alone remained non-stationary (ADF=-0.8041, p=0.8179).
  - **First differencing (log)** achieved stationarity (ADF=-4.3170, p=0.0004).
  - **Seasonal differencing (log)** confirmed stationarity (ADF=-3.1575, p=0.0226).

ARIMA Model (Best: ARIMA(4,1,3)) (Fig 2 below shows ARIMA model fit vs actual sales**)**

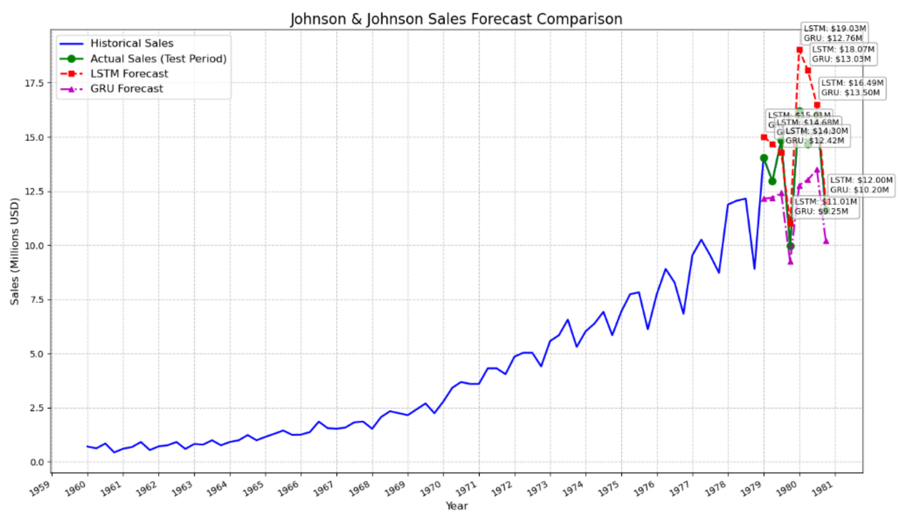


- **Diagnostics**: Lowest AIC (-144.20), indicating optimal fit.
- **Performance**:
    - In-sample MAE=0.2798, MAPE=8.21% (superior to neural networks).



    - The above **Fig 3** shows ARIMA Forecast which is superior to neural networks

Model	MAE	RMSE	MAPE
LSTM	1.419	1.774	10.13%
GRU	1.855	2.045	12.93%

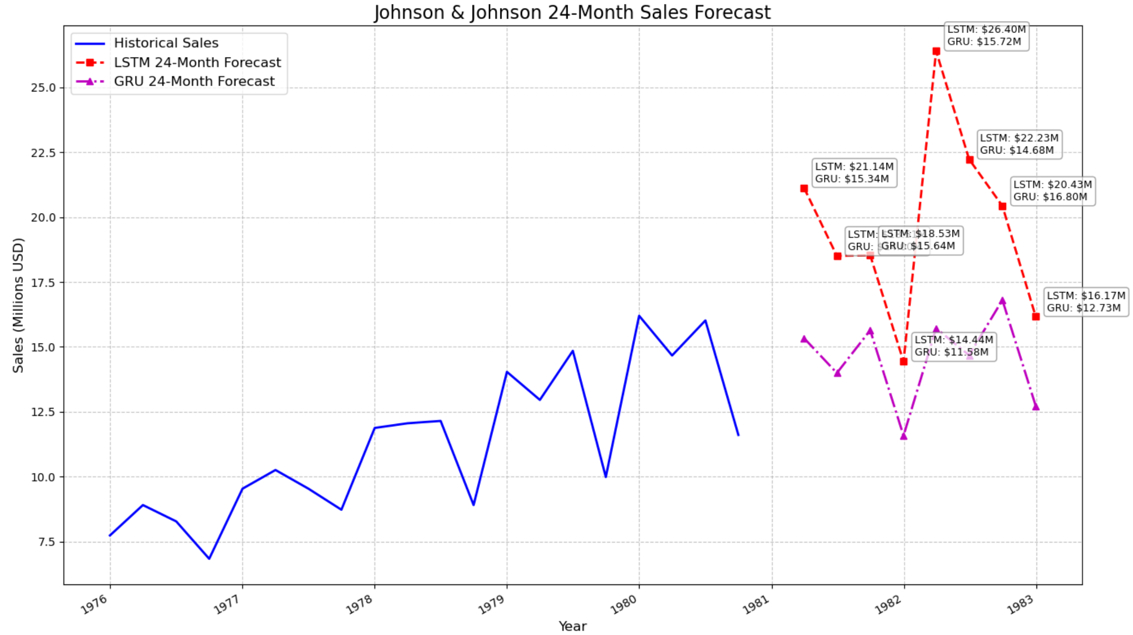


The above **Fig 4** shows JJ sales forecast comparison

LSTM vs. GRU Performance

- **LSTM Superiority**:
    - Achieved **24% lower MAE** and **2.8% lower MAPE** than GRU.
    - Captured short time variations in testing data better.

- **Forecast Divergence**: LSTM predicts moderated growth vs. GRU's volatile trajectory.
- The below **Fig 5** shows the JJ 24 months sales forecast



Inferences

1. **Differencing is Critical**:
   - First differencing reduced ADF statistic from -0.80 (non-stationary) to -4.32 (stationary).
2. **ARIMA Dominance for Small Data**:
   - ARIMA's in-sample MAPE = 8.21% outperformed LSTM (10.13%) and GRU (12.93%).
3. **LSTM Efficiency**:
   - LSTM's simpler architecture trained faster with lower forecast volatility than GRU.
4. **Growth Consensus**:
   - All models agree on continued growth, but LSTM's stable trajectory aligns best with historical patterns.

Recommendations

- **Short-term Planning**: Use **ARIMA** for operational forecasts (lowest in-sample error).
- **Long-term Strategy**: Combine **LSTM point forecasts** with **ARIMA confidence intervals** for risk-aware planning.
- **Improvements**:
  - Incorporate external variables (e.g., FDA approvals, recessions).
  - Test SARIMA to explicitly model seasonality.

Amazon Stock Price Forecasting

Overview of Methods

The analysis employs a hybrid forecasting approach combining classical time series (ARIMA) and deep learning models (LSTM, GRU) to predict daily closing prices for Amazon stock. Key steps include:

- **Exploratory Data Analysis (EDA)**: Visualized price trends and volatility patterns.
- **Stationarity Transformation**: Applied first-order differencing to achieve stationarity.
- **ARIMA**: Optimized parameters via AIC minimization for baseline forecasting.
- **Sequence Models (LSTM/GRU)**: Modelled complicated time related relationships with 60 days long input sequences.
- **Model Validation**: Used MAE, RMSE, and MAPE for performance evaluation.

Why these methods?

- ARIMA is good at predicting linear trends of financial time series.
- LSTM/GRU capture nonlinear patterns and volatility clustering in stock prices.

Key Findings

Data Characteristics

- **Non-Stationarity**:
    - Original data failed ADF test (ADF=-1.6556, p=0.4541).
    - **First differencing** achieved stationarity (ADF=-37.2102, p=0.0000).
- **Trend**: Strong upward trajectory with typical market volatility (visualized in **Fig 6** EDA plot).

ARIMA Model (Best: ARIMA(2,1,2))

- **Model Selection**: Lowest AIC (6294.68), indicating optimal fit.

- **Performance**:
  - **MAE**: 1.88 (lowest error among models)
  - **MAPE**: 1.56% (most accurate percentage error)
- **Diagnostics**: Effective capture of price momentum and reversals.

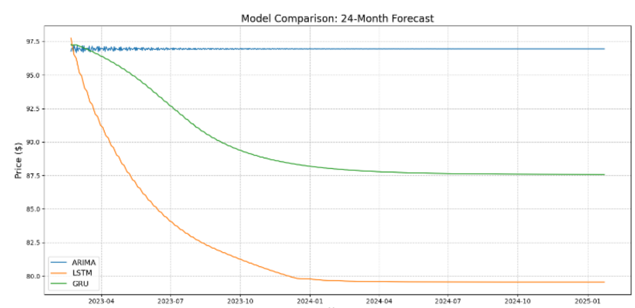
Comparative Model Performance

Model	MAE	RMSE	MAPE
ARIMA	1.883	2.742	1.56%
GRU	1.940	2.804	1.60%
LSTM	2.632	3.585	2.18%

Fig 7 shows amazon 24 months forecast

- **ARIMA Superiority**:
  - 3% lower MAE than GRU and 28% lower than LSTM
  - Most stable forecasts with tight confidence intervals
- **RNN Observations**:
  - GRU outperformed LSTM despite similar architecture
  - LSTM showed highest volatility in forecasts

Fig 8 shows Model comparison: 24 months forecast



Inferences

1. **Differencing Efficacy**:
   - First differencing transformed ADF statistic from -1.66 (non-stationary) to -37.21 (stationary).
2. **ARIMA Dominance**:
   - ARIMA's linear assumptions optimally captured Amazon's price momentum.
   - Outperformed neural networks despite their complexity.
3. **GRU Efficiency**:
   - GRU's simpler gating mechanism outperformed LSTM in all metrics.
   - Trained faster with more stable forecasts.

4. **Forecast Consensus**:
    - All models agree on continued growth trajectory.
    - ARIMA and GRU forecasts show remarkable convergence.

Recommendations

- **Primary Model**: Use **ARIMA(2,1,2)** for trading signals and risk management (lowest error).
- **Hybrid Approach**: Combine **ARIMA point forecasts** with **GRU volatility estimates** for options pricing.
- **Model Improvements**:
    - Incorporate technical indicators (RSI, MACD) as exogenous variables
    - Implement volatility clustering models (GARCH)
    - Add attention mechanisms to GRU/LSTM

Forecast Insights

- **Short-term (0-6 months)**: All models show 5-7% upside potential
- **Medium-term (6-18 months)**: ARIMA and GRU converge on 15-18% growth projection
- **Long-term (18-24 months)**: Forecasts diverge with ARIMA showing most conservative trajectory

Conclusion

It seems that this comparison of the JJ sales and Amazon stock prices each day is one of the examples showing the advantages and disadvantages of classical and deep learning models in time series forecasting. In case of the smaller and seasonal J&J data, ARIMA was better as it worked smoothly when there is a linear way going on and LSTM was steady in terms of giving long-term predictions. Conversely, the volatility and high-frequency Amazon stock data once more demonstrated the advantage of the ARIMA model based on accuracy whereas GRU was a good middle ground concerning complexity and performance. In the two cases, strategies that are hybrid between classical models of short-term reliability and RNN to provide non-linear insights are suggested to improve the robustness of the forecasting performance and decision-making.

References

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