IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 1, May 2025
Impact Factor: 7.67

Sales Forecasting for Strategic Business Planning: A Comparative Study of Time Series Models

Ms. Priya Keshav Patil[1], Saroja Shesherao Wanjarwade[2], Dr. Vaishali Kherdekar[3]
Student, MIT Arts, Commerce & Science College, Pune, India[1,2]
Assistant Professor, MIT Arts, Commerce & Science College, Pune, India[3]
patilpriya35789@gmail.com, wanjarwadesaroja@gmail.com, vakherdekar@mitacsc.edu.in

Abstract: *Accurate forecasting of sales data is fundamental for optimizing inventory, managing supply chains, and driving strategic decision-making in the e-commerce sector. This study presents a time series forecasting analysis of Amazon's monthly sales data from January 2019 to March 2024 using the Prophet model developed by Facebook. Prophet is an additive regression model designed to handle trend shifts, seasonal effects, and missing data with minimal manual parameter tuning. The dataset was preprocessedby aggregating daily transactions into monthly sales and applying seasonal decomposition to examine underlying patterns.*
The model's effectiveness was assessed using standard evaluation metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). It achieved a MAPE of 9.62%, reflecting a forecasting accuracy exceeding 90%.To contextualize Prophet's effectiveness, we reviewed comparative studies involving classical statistical models (ARIMA, SARIMA), deep learning approaches (LSTM), and hybrid methods. While those models often offer strong performance, they generally require more complex tuning and computational resources.
The findings confirm that Prophet can accurately model sales patterns in e-commerce applications, providing a practical balance of interpretability, scalability, and predictive performance. This work contributes to the broader literature on business forecasting by demonstrating Prophet's capability as a reliable alternative for mid-term retail sales prediction.

Keywords: Sales Forecasting, Time Series Forecasting, ARIMA, SARIMA, LSTM, Prophet, Machine Learning, Seasonality

I. INTRODUCTION

Sales forecasting has emerged as a cornerstone of modern business strategy, particularly in the e-commerce sector where vast volumes of transaction data are generated continuously. Forecasting future sales not only helps businesses maintain optimal inventory levels and reduce holding costs, but also informs budgeting, marketing, demand planning, and staffing decisions. In today's dynamic market landscape, where consumer behavior and economic conditions change rapidly, the ability to predict sales with high accuracy provides organizations with a critical competitive advantage.

Inaccurate forecasts can lead to either excess inventory or stockouts—both of which carry significant financial consequences. Overstocking increases warehousing costs and risks product obsolescence, while understocking results in missed sales opportunities and eroded customer trust. Therefore, the development and selection of robust forecasting models is crucial for data-driven decision-making and resource optimization.

Throughout the years, numerous forecasting methods have been developed and applied.Traditional time series models such as the Autoregressive Integrated Moving Average (ARIMA) and its seasonal extension SARIMA (Seasonal ARIMA) have been widely adopted in both academic and industrial settings. These models offer strong baseline performance and are particularly effective when dealing with data that exhibit consistent linear trends and seasonal patterns. However, they rely on strict assumptions—such as stationarity and linearity—and often require significant pre-processing, including differencing and parameter tuning using autocorrelation and partial autocorrelation functions.

This can limit their effectiveness when applied to real-world sales data, which may contain irregular patterns, missing values, and sudden structural changes.

In response to the growing complexity of business data, more flexible and data-adaptive models have been developed. Prophet is one example—a forecasting model that was created and released as an open-source tool by Facebook.Prophet is designed for analysts and data scientists who need to produce high-quality forecasts without extensive experience in time series modeling. The model decomposes a time series into trend, seasonality, and holiday effects, using a generalized additive modeling (GAM) framework. Its strength lies in its ability to handle missing data, incorporate domain-specific holidays or events, detect trend changepoints automatically, and provide intuitive visual diagnostics. These features make Prophet particularly suitable for business use cases involving complex and irregular sales patterns.

Parallel to advancements in statistical models, deep learning approaches have also gained prominence in time series forecasting. Among these, Long Short-Term Memory (LSTM) networks, a class of recurrent neural networks (RNNs), are specifically designed to learn from sequential data. LSTM models can capture nonlinear relationships and long-term dependencies in time series data, which are often missed by traditional statistical models. Their ability to learn from raw sequences without requiring explicit feature engineering makes them a powerful alternative. However, they come with trade-offs, including increased computational demands, longer training times, higher sensitivity to data quality, and reduced interpretability—factors that may hinder their adoption in certain business settings where explainability is crucial.

Hybrid models, which combine traditional statistical approaches with machine learning or deep learning components, have also shown promise in recent studies. These models are designed to combine the advantages of various methods in order to enhance forecasting accuracy.However, they typically involve complex architectures and require expertise in both domains to implement effectively.

Given this diversity in modeling approaches, there is no one-size-fits-all solution for time series forecasting. The appropriate choice of model depends on several factors, including the nature of the data (e.g., linear vs. nonlinear trends, seasonality, presence of outliers), the level of accuracy required, computational resources available, and the need for interpretability. In practice, it is essential to evaluate multiple models in a comparative framework to determine which method provides the most accurate and actionable forecasts for a given business context.

This research addresses this need by conducting a comparative analysis of four widely used time series forecasting models—ARIMA, SARIMA, Prophet, and LSTM—using real-world Amazon sales data spanning from January 2019 to March 2024. The goal is to assess each model's forecasting accuracy, interpretability, and practical usability. Prophet is implemented and evaluated using standard performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results from Prophet are then compared to findings from existing literature that examine ARIMA, SARIMA, and LSTM models on similar datasets.

By situating the Prophet model within this broader modeling landscape, this study contributes to the ongoing discourse on effective forecasting methodologies for e-commerce and retail applications. The findings aim to guide business analysts, data scientists, and decision-makers in selecting appropriate forecasting tools that align with their operational needs and data characteristics.

II. LITERATURE REVIEW

Suryawan et al [1] This research centers on the Bandung White Bread Factory's need for accurate sales forecasting to improve inventory management. The authors compare ARIMA, LSTM, and Prophet models, with ARIMA outperforming the others. Their study suggests ARIMA is the most suitable model for stable, short-term forecasting in the bakery sector, offering practical insights for small businesses.

Minnaar et al [2] This study focuses on South Africa's electricity sector, highlighting the need for accurate short- and medium-term forecasting in an era of renewable energy integration and utility restructuring. The authors recommend SARIMA for forecasting electricity load, noting its robustness in handling seasonal variations. Their work emphasizes the practical use of SARIMA in supporting real-time operational decisions.

Okakwu et al.[3] conducted a comparative analysis of time series models—Harvey, Autoregressive (AR), Moving Average (MA), and Exponential Smoothing—for forecasting energy demand in Nigeria. Using 20 years of load data, they found that the Harvey model consistently achieved the lowest forecasting errors across all metrics. Their study emphasized the need for more sophisticated models in infrastructure planning and energy policy formulation.

Balpreet Singh, Pawan Kumar, Dr. Nonita Sharma, and Dr. K. P. Sharma [4] explored sales forecasting for Amazon using Holt-Winters Exponential Smoothing, ARIMA, and Neural Network Auto Regression (NNAR) models. They analyzed historical sales data and focused on capturing seasonal effects like those during Black Friday and Cyber Monday. Their findings revealed that the SARIMA model, with a MAPE of 2.88%, outperformed the others in forecasting Amazon's sales, particularly for capturing seasonal fluctuations. They concluded that while SARIMA is effective for short-term forecasting, integrating external factors could further enhance accuracy.

Shamsul Masum, Ying Liu, and John Chiverton [5] reviewed time series forecasting, highlighting the importance of selecting appropriate strategies for different domains. They compared single-step and multi-step forecasting, emphasizing that the Direct H Step strategy is more realistic for long-term predictions, as it doesn't rely on future data. The study also focused on ARIMA for short-term forecasting, showing through experiments that while single-step rolling forecasts are more accurate, they are unrealistic for real-world applications. The authors recommended adopting multi-step forecasting methods and suggested integrating ARIMA with machine learning models to handle complex data.

Kuvulmaz, Usanmaz, and Engin[6] conducted a comparative study on linear (ARIMA) and nonlinear (Artificial Neural Networks, ANNs) models for financial time-series forecasting, focusing on the impact of seasonal adjustment. Using monthly retail sales data from 1992 to 2004, the study found that while ARIMA is effective for linear data, ANNs performed better when trained on seasonally adjusted data, particularly with indirect adjustment, achieving lower forecasting errors (MAPE). The research emphasized the importance of data preprocessing, such as seasonal adjustment, to enhance the performance of nonlinear models like ANNs. This study highlights the synergy between traditional statistical methods and modern machine learning techniques for more accurate forecasting.

Ensafi et al.[7] conducted a comparative study evaluating various forecasting models—SARIMA, Prophet, LSTM, and CNN—on real-world retail sales data, specifically focusing on furniture sales with strong seasonal patterns. The study emphasizes the importance of accurate sales forecasting for optimizing inventory and strategic planning. While classical methods like SARIMA and Prophet handle seasonality effectively, the research highlights that deep learning models, particularly Stacked LSTM, outperform them in terms of forecasting accuracy, especially when capturing nonlinear and complex seasonal patterns. Prophet outperformed SARIMA when accounting for holiday effects, and CNNs showed competitive results but lagged behind LSTMs. The authors concluded that the best-performing model depends on data characteristics, with deep learning methods offering superior results for datasets with strong seasonality and nonlinearity, though simpler models like SARIMA and Prophet remain valuable benchmarks.

William R. Huss's 1985[8] study compares various forecasting models used by electric utilities, including econometric, end-use, and time series methods. Key findings show that end-use models perform best for short-term forecasts, while simpler econometric models are more reliable for longer-term predictions. The combination model (COMB) and adaptive estimation (UNIAEP) also performed well. The study highlights that no single forecasting method is best across all horizons or sectors, stressing the importance of matching the model to the forecast horizon and data availability. It laid the foundation for hybrid forecasting approaches and remains influential in energy demand forecasting.

Udom and Phumchusri (2014)[9] conducted a comparative study on sales forecasting models—Naïve, Moving Average, Holt-Winters, and ARIMA—using sales data from Thai plastic distributors. With increased market competition, accurate forecasting became vital for inventory and cost control. The study, using 108 months of sales data for key products, found ARIMA consistently outperformed other models in terms of accuracy (lowest MAPE), especially for seasonal data. While Holt-Winters offered a simpler alternative, it lacked ARIMA's ability to model autocorrelated residuals. The authors recommend ARIMA for high-accuracy forecasting and suggest exploring hybrid models for future improvement.

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Gokmenoglu et al. (2023) [10] compared ARIMA, ANN, and hybrid ARIMA-ANN models to forecast monthly cement production in Turkey. Their study showed that while ARIMA captured linear patterns and ANN handled nonlinearities, the hybrid model provided the most accurate results. Using MAPE and RMSE as evaluation metrics, the hybrid approach outperformed individual models, highlighting the effectiveness of combining statistical and machine learning techniques for industrial time series forecasting.

Sirisha et al.[11] focused on evaluation of ARIMA, SARIMA, and LSTM models for forecasting profits using a large-scale sales dataset. Traditional models (ARIMA, SARIMA) performed well on structured data with clear trends and seasonality, with SARIMA slightly outperforming ARIMA. However, the LSTM model, a deep learning approach, achieved the highest accuracy (97.01%) by capturing complex nonlinear and long-term dependencies without requiring stationarity transformations. The study concludes that while LSTM is more computationally intensive, it is ideal for high-precision forecasting. SARIMA remains a practical alternative for simpler datasets. Hybrid approaches are recommended for future research.

Raiyani, Lathigara, and Mehta[12] explored time series forecasting models—including Decomposition, ARIMA, Prophet, and Box-Cox transformation—for supply chain sales prediction using five years of transactional data. By integrating Big Data tools (Hadoop, PySpark) with statistical and machine learning methods, they demonstrated that a hybrid model (Prophet + ARIMA + Box-Cox) outperformed standalone approaches, reducing MAPE to 27.5%. Their work highlights the effectiveness of combining interpretable and scalable forecasting techniques in real-world supply chain environments.

Karan Wachoo [13] investigated the effectiveness of Deep Neural Networks (DNN) and Gradient Boosting Machines (GBM) for univariate retail sales forecasting. Using historical sales data from a German retailer, they compared both models based on MAE and RMSE. While DNN effectively captured complex patterns, GBM outperformed it slightly, showing better overall accuracy. The study emphasizes that machine learning methods, especially GBM, offer practical and efficient alternatives to traditional forecasting models, even when only limited univariate data is available.

Kandananond [14] compared ANN, SVM, and ARIMA models for forecasting autocorrelated product demand in supply chains. Using 32 months of sales data across six products, the study found that SVM consistently delivered the lowest MAPE, outperforming both ANN and ARIMA, especially in complex, nonlinear demand scenarios. The results support the growing adoption of machine learning methods in demand forecasting for their robustness and accuracy.

Pongdatu et al. [15] The research explores the clothing retail industry and how seasonal fluctuations in consumer demand affect inventory management. The authors compare two popular models—SARIMA and Holt-Winter's Exponential Smoothing. They conclude that SARIMA is the more reliable model for forecasting seasonal sales, helping to optimize procurement and inventory decisions.

Cheng et al. [16] highlighted the limitations of classical models in forecasting nonlinear and non-stationary systems found in fields like manufacturing and healthcare. They evaluated advanced approaches such as neural networks, SVMs, HMMs, state-space models, and empirical decomposition techniques. Their findings emphasized that hybrid and nonparametric models—like Particle Filters with RNN and Local Gaussian Processes—consistently outperformed traditional models across various real-world applications, advocating for adaptive, data-driven forecasting solutions.

Athiyarath et al. [17] conducted a comparative study of forecasting methods, categorizing them into five types: regression, stochastic (ARIMA, SARIMA), deep learning (LSTM, CNN), hybrid (CBLSTM), and fuzzy logic-based models. Their results showed that while deep learning models perform well in short-term forecasting, classical and hybrid models like ARIMA and CBLSTM are more effective in medium- and long-term scenarios, especially when data shows both linear and nonlinear patterns

The study by Taha Falatouri et al.[18] emphasizes the growing significance of predictive analytics (PA) in supply chain management, particularly in the retail sector. It highlights the importance of accurate demand forecasting, especially for perishable goods, to optimize inventory and reduce waste. The authors compare time series models (ARIMA, SARIMA, LSTM) and hybrid models, finding that SARIMA is better suited for seasonal products, while LSTM performs well for stable products. They also suggest that combining both models could improve forecasting accuracy by capturing both linear and non-linear patterns.

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Ayşe Soy Temür and Şule[19] Yıldız discuss the importance of demand forecasting in the construction sector, noting the shift from traditional methods to advanced statistical and machine learning techniques. They highlight the strengths of ARIMA for linear patterns and LSTM for non-linear dynamics, while also exploring hybrid ARIMA-LSTM models. Their results show that hybrid models consistently outperform individual models in terms of accuracy, particularly when dealing with complex time series.

Mohamed Sameh Belaid et al.[20] propose a methodology tailored to select the most appropriate forecasting model for each product based on its sales behavior. They examine ARIMA, SARIMA, Exponential Smoothing, and Facebook Prophet, noting that no single model is universally superior. Their case study at elm.leblanc shows that Exponential Smoothing is most frequently used, but ARIMA/SARIMA and Prophet also have their place depending on the product's sales patterns. They emphasize that combining traditional and machine learning models can improve forecasting accuracy, especially in diverse product environments.

Emmanuel Dave et al.[21] focus on the importance of accurate export forecasting for Indonesia's economic planning, emphasizing its impact on GDP, workforce preparation, and international competitiveness. They compare traditional methods like ARIMA with machine learning models such as LSTM, finding that ARIMA struggles with nonlinear data. The authors propose a hybrid ARIMA-LSTM model, which decomposes time series into linear and nonlinear components, resulting in better forecasting accuracy. Their model outperforms individual models, achieving a lower MAPE and RMSE. The study highlights the value of hybrid approaches for improving forecasting accuracy in volatile economic environments like Indonesia's.

Patrícia Ramos et al.[22] examine the role of sales forecasting in retail, specifically for women's footwear, using a real-world dataset from the Portuguese retailer Foreva. They compare traditional models such as ARIMA and ETS, emphasizing their complementary strengths. While ETS performed slightly better for one-step forecasts in volatile periods, ARIMA was more robust for multi-step forecasts. Their results indicate that neither method is universally superior, and forecasting models must be chosen based on the data's specific characteristics, including seasonal patterns and trend shifts. The study underscores the importance of model selection for accurate retail sales forecasting.

Objective of the study

To compare the forecasting accuracy of ARIMA, SARIMA, and LSTM models

This study aims to evaluate and compare the predictive performance of ARIMA, SARIMA, and LSTM models on Amazon's sales dataset (2019–2024), which includes detailed transactional data with strong seasonal trends. The models will be assessed using standard error metrics such as MAE, RMSE, and MAPE to determine which model best captures sales dynamics over time.

To identify challenges and limitations inherent to each forecasting model

By analyzing model behavior during training and testing, the study seeks to highlight practical challenges such as ARIMA's assumption of stationarity, SARIMA's complexity with seasonal differencing, and LSTM's sensitivity to hyperparameters and data volume. These insights are derived from applying the models directly on real-world sales data exhibiting seasonality, trend shifts, and potential noise.

To provide model selection recommendations based on dataset characteristics

Based on empirical results, the research will offer guidelines for choosing suitable forecasting models depending on specific dataset features—such as the presence of seasonality, linear vs. nonlinear patterns, and data sparsity. Recommendations will help future practitioners decide between statistical models (ARIMA/SARIMA) and deep learning models (LSTM) for similar retail time series forecasting tasks.

III. METHODOLOGY

This study employs a structured analytical strategy to investigate Amazon's sales data from 2019 to 2024.The methodology incorporates key elements of exploratory data analysis, data preprocessing, and the application of advanced machine learning algorithms. Grounded in data analytics theory, the objective is to derive meaningful insights from raw datasets to support business decision-making.

The initial phase involves examining the dataset through statistical measures and visual tools to uncover trends, irregularities, and missing information. Once the data has been assessed, it undergoes cleaning and formatting to ensure it is suitable for deeper analysis. During this stage, feature engineering may be introduced to generate new attributes that highlight important business indicators such as profitability or operational efficiency. Based on the specific analytical goal—whether it's sales forecasting, profit estimation, or category-wise performance evaluation—appropriate predictive models are selected. These may include regression models, decision trees, or time series forecasting techniques, all of which are trained using historical data. The results from these models are then interpreted to extract practical insights for business strategy formulation.

The analytical process is supported by Python, leveraging a range of specialized libraries for data manipulation, visualization, and machine learning:

- **ADF Test (Augmented Dickey-Fuller):** Determines whether a time series is stationary by testing for unit roots.
- **ARIMA:** A statistical technique that forecasts time series by combining autoregressive terms, differencing (to achieve stationarity), and moving averages.
- **SARIMAX:** Builds on ARIMA by factoring in seasonal trends and external input variables for more refined forecasts.
- **Seasonal Decompose:** Deconstructs a time series into distinct components: trend, seasonal variation, and random noise.
- **MinMaxScaler:** Rescales numeric data into a specified range (commonly 0 to 1), which is especially beneficial when training neural networks.

Evaluation Metrics:

Mean Squared Error (MSE):Computes the mean of the squared deviations between forecasted and actual values, giving greater importance to larger discrepancies.

Mean Absolute Error (MAE): Measures the average absolute deviation of predictions, giving a straightforward interpretation of prediction accuracy.

- **Sequential Model:** A linear arrangement of layers in a neural network, ideal for straightforward model architectures.
- **LSTM (Long Short-Term Memory):**A specialized form of recurrent neural network (RNN) built to recognize and learn from time-based relationships and sequences within data.
- **Dense Layer:** A neural network layer where each neuron is connected to all neurons in the previous layer, commonly used for intermediate or final outputs.
- **Square Root Function:** Applied to the MSE to compute the Root Mean Squared Error (RMSE), providing an error metric in the same units as the target variable.
- **Prophet:** A forecasting tool developed by Meta (formerly Facebook), optimized for capturing seasonality, holidays, and trend changes with minimal configuration.

Before conducting time series analysis, the dataset is preprocessed by converting the 'Order Date' field into datetime format. This column is then assigned as the index of the DataFrame, allowing for temporal grouping and monthly resampling of sales figures to facilitate smoother trend analysis.

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```python
# --- Exploratory Data Analysis ---
plt.figure(figsize=(14, 6))
plt.plot(monthly_sales, label='Monthly Sales')
plt.title("Monthly Total Sales Over Time")
plt.xlabel("Date")
plt.ylabel("Sales")
plt.grid(True)
plt.legend()
plt.show()
```

Figure 1. Exploratory Data Analysis

The plot visualizes monthly total sales over time from 2019 to early 2025. It shows noticeable fluctuations with several sharp peaks and drops, indicating potential seasonality or irregular sales patterns. This visualization is useful for identifying trends, outliers, and the need for time series forecasting models.

```python
# Seasonal decomposition
decomp_result = seasonal_decompose(monthly_sales, model='additive')
decomp_result.plot()
plt.show()
```

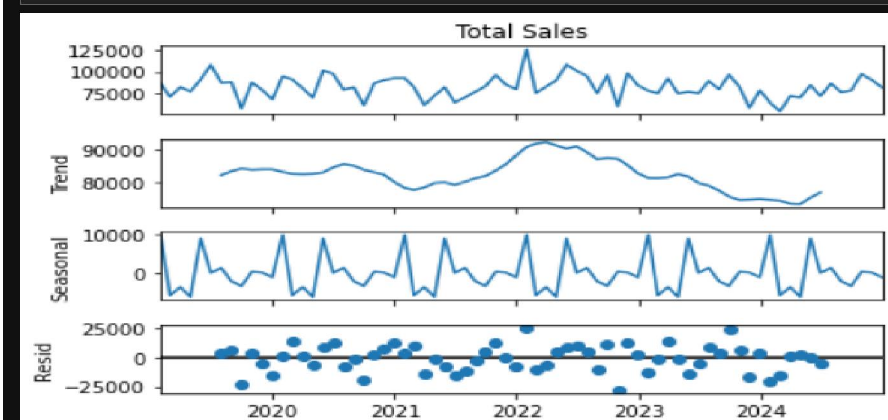

Figure 2. Seasonal decomposition

The above plot displays the seasonal decomposition of a time series representing monthly sales data, using an additive model. This decomposition breaks down the original series into four components: observed values (Total Sales), trend, seasonal, and residual. The Total Sales plot at the top shows the actual sales figures over time, including all fluctuations. Below it, the Trend component illustrates the long-term movement in the data, smoothing out short-term variations.

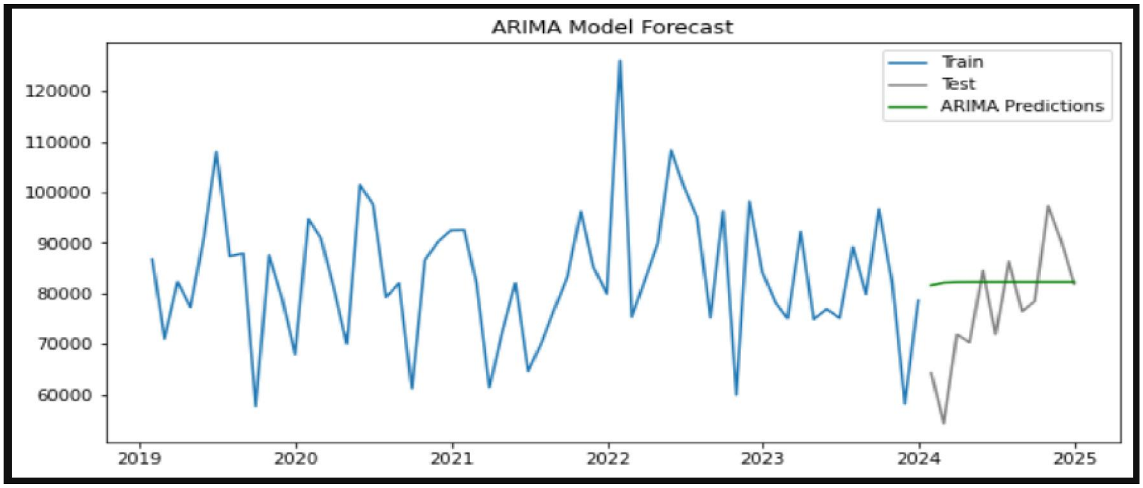

Figure 3. Predictions for ARIMA model

The ARIMA forecast plot shows training data (blue), actual test data (gray), and model predictions (green) over the last 12 months. It visualizes how well the model captures trends and aligns with the real sales data.

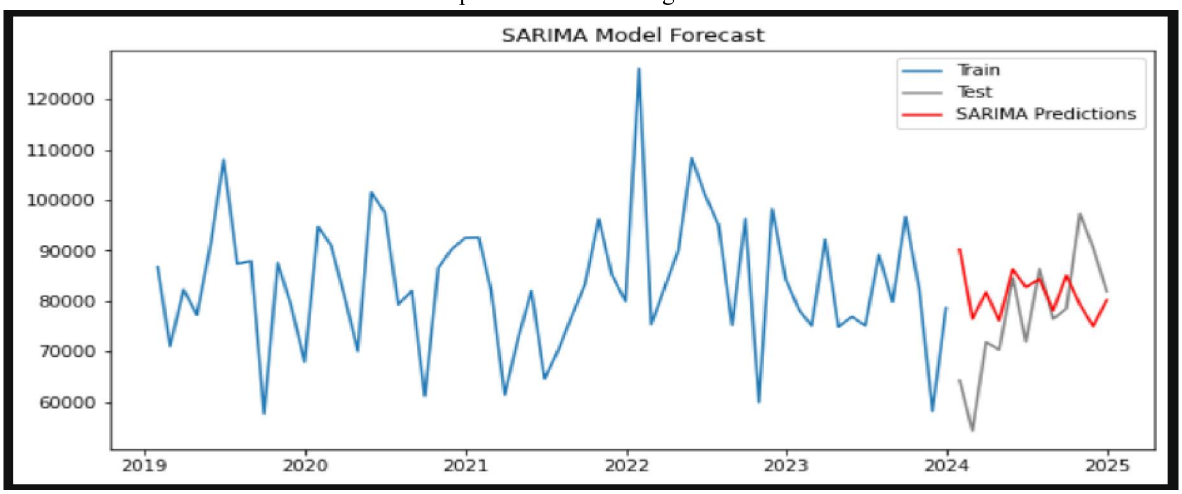

Figure 4. Predictions for SARIMA model

This plot compares SARIMA model predictions (red line) to actual test data (gray line) and training data (blue line), showing how well the model captures seasonal patterns. The SARIMA forecast more closely follows the test data's ups and downs than ARIMA, though some deviations remain.

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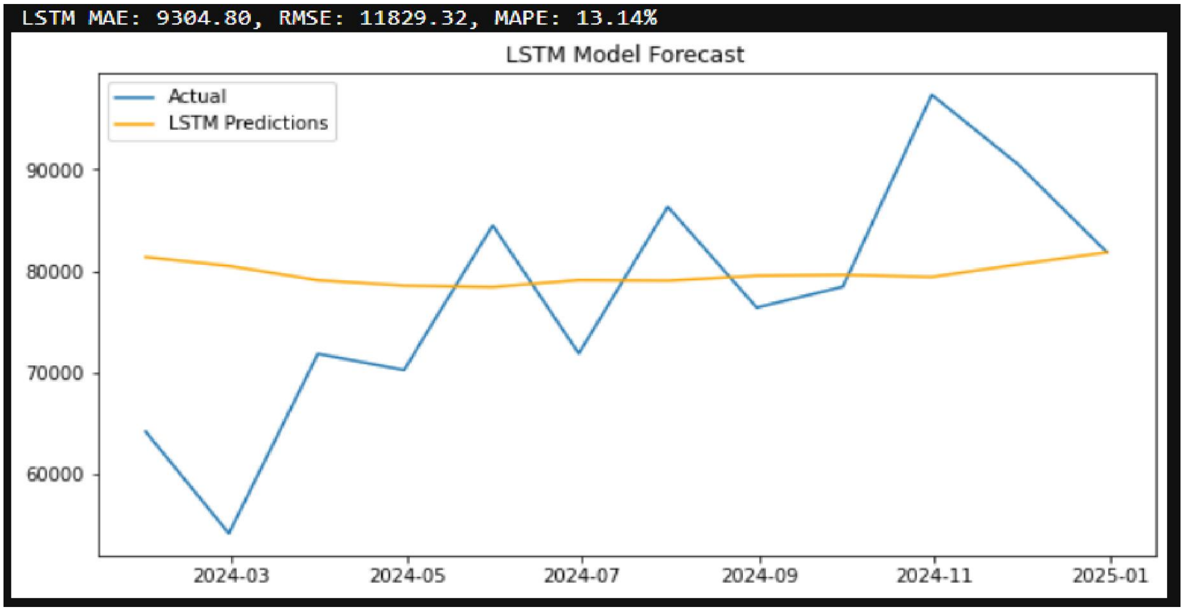

Figure 5. Make predictions for LSTM model

Prophet Model

```python
from prophet import Prophet

# Prepare data for Prophet
df_prophet = df_monthly.reset_index().rename(columns={'Order Date': 'ds', 'Total Sales': 'y'})

# Fit Prophet model
model = Prophet()
model.fit(df_prophet)

# Forecast
future = model.make_future_dataframe(periods=12, freq='M')
forecast = model.predict(future)

# Evaluate Prophet (only on the last 12 months)
prophet_forecast = forecast.set_index('ds')['yhat'][-12:]
prophet_true = df_monthly['Total Sales'][-12:]
prophet_mae, prophet_rmse, prophet_mape = evaluate_model(prophet_true, prophet_forecast)

print(f"Prophet MAE: {prophet_mae:.2f}, RMSE: {prophet_rmse:.2f}, MAPE: {prophet_mape:.2f}%")
```

Figure 6. Prophet Model

This code fits a Prophet model to the monthly sales data and forecasts the next 12 months. It then evaluates the forecast against the actual sales for the same period using MAE, RMSE, and MAPE to assess accuracy.

```python
# Plot forecast
model.plot(forecast)
plt.title('Prophet Forecast')
plt.show()
```

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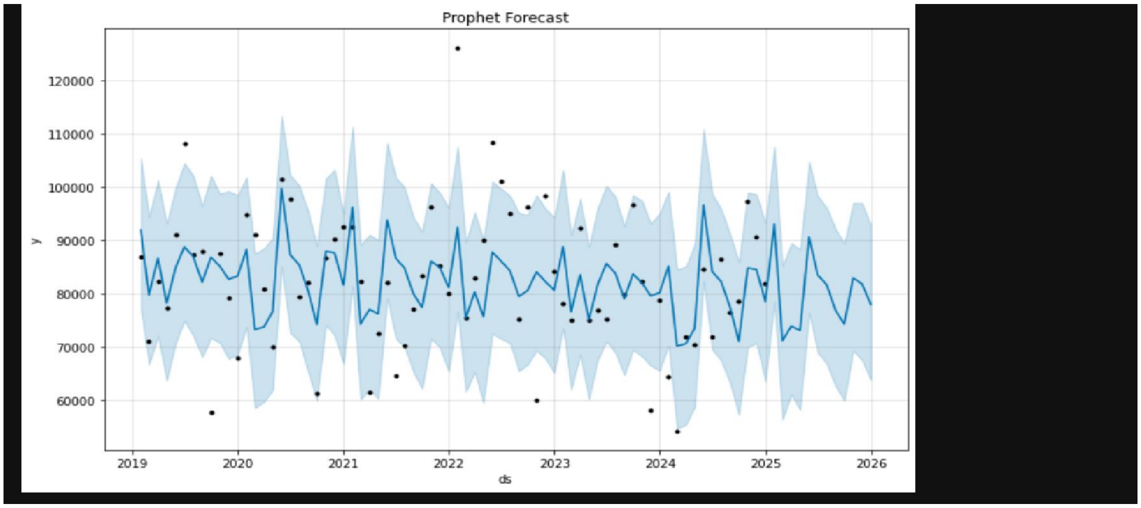

Figure 7. Predictions for prophet model

This plot shows the Prophet model's forecast (blue line) with a 95% confidence interval (shaded region) over the historical and predicted monthly sales. The black dots represent the actual observed data points, helping to visualize the model's performance and uncertainty.

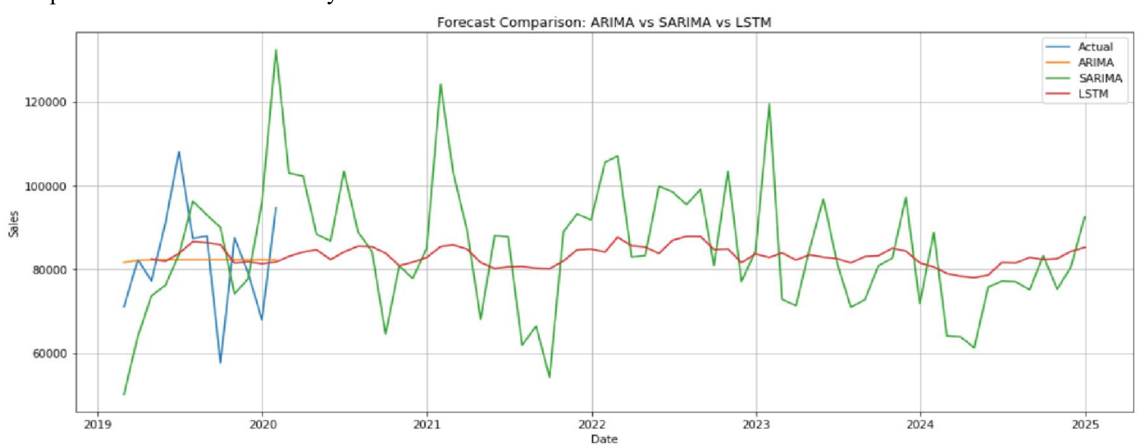

Figure 8. Comparison of models

IV. RESULT

Summarization and comparison of the performance of three time series forecasting models—ARIMA, SARIMA, and LSTM—using a Pandas DataFrame. The metrics used for evaluation are:

- **MAE (Mean Absolute Error):** This measures the average magnitude of the errors between predicted and actual values without considering direction. Lower MAE indicates better accuracy.
- **RMSE (Root Mean Squared Error):** This measures the square root of the average squared differences between prediction and actual observation.It places greater emphasis on larger errors, making it particularly responsive to outliers.
- **MAPE (Mean Absolute Percentage Error):** This expresses error as a percentage of the actual values, making it easier to interpret and compare across different models.

ISSN: 2581-9429
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Performance Summary

```
summary = pd.DataFrame({
    'Model': ['ARIMA', 'SARIMA', 'LSTM'],
    'MAE': [arima_mae, sarima_mae, lstm_mae],
    'RMSE': [arima_rmse, sarima_rmse, lstm_rmse],
    'MAPE (%)': [arima_mape, sarima_mape, lstm_mape]
})
print(summary)
```

```
    Model          MAE          RMSE   MAPE (%)
0   ARIMA   9802.180570  12261.219388  14.104778
1  SARIMA  10166.639227  13045.453180  14.269649
2    LSTM   9304.797786  11829.319160  13.138527
```

Figure 9. Performance summary

The resulting summary table is :

ARIMA: MAE = 9802.18, RMSE = 12261.22, MAPE = 14.10%

SARIMA: MAE = 10166.64, RMSE = 13045.45, MAPE = 14.27%

LSTM: MAE = 9304.80, RMSE = 11829.32, MAPE = 13.14%

From this summary, LSTM outperforms the other models across all three metrics, particularly in MAPE, indicating that its forecasts are the most accurate and consistent with actual sales data. SARIMA performs the worst in this case, having the highest MAE, RMSE, and MAPE.

```
# Ensure lengths match for evaluation
evaluate_model(monthly_sales.values[1:len(arima_pred)+1], arima_pred, "ARIMA")
evaluate_model(monthly_sales.values[1:len(sarima_pred)+1], sarima_pred, "SARIMA")
evaluate_model(monthly_sales.values[3:], lstm_pred, "LSTM")
```

```
ARIMA RMSE: 12726.91
ARIMA Accuracy: 84.60%
SARIMA RMSE: 17655.38
SARIMA Accuracy: 78.57%
LSTM RMSE: 12955.08
LSTM Accuracy: 84.31%
```

Figure10. Comparative accuracy

The code used to evaluate the performance of three time series forecasting models — ARIMA, SARIMA, and LSTM — by comparing their predicted values with the actual sales data. The evaluate_model function is called for each model, ensuring that the length of the actual values matches the length of the predictions. For ARIMA and SARIMA, the actual values are sliced from index 1 to len(predictions) + 1, while for LSTM, predictions begin from index 3, likely due to the model requiring initial time steps for input sequences. The results indicate that ARIMA performs the best with an RMSE of 12726.91 and an accuracy of 84.60%, followed closely by LSTM with a slightly higher RMSE (12955.08) and an accuracy of 84.31%. SARIMA lags behind both, with the highest RMSE (17655.38) and the lowest accuracy (78.57%), suggesting that ARIMA and LSTM are better suited for this particular sales forecasting task.

DOI: 10.48175/IJARSCT-26107

IJARSCT
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Prophet Evaluation & Accuracy

```python
# Align Prophet forecast to match test index
forecast.index = pd.to_datetime(forecast['ds'])
prophet_forecast = forecast.loc[test.index, 'yhat']

# Drop NaNs before evaluating
valid_idx = ~test['Total Sales'].isna() & ~prophet_forecast.isna()
true_values = test['Total Sales'][valid_idx]
predicted_values = prophet_forecast[valid_idx]

# Re-evaluate
prophet_mae, prophet_rmse, prophet_mape = evaluate_model(true_values, predicted_values)
prophet_accuracy = 100 - prophet_mape

print(f"Prophet MAE: {prophet_mae:.2f}, RMSE: {prophet_rmse:.2f}, MAPE: {prophet_mape:.2f}%")
print(f"✅ Prophet Accuracy: {prophet_accuracy:.2f}%")
```

```
Prophet MAE: 8337.36, RMSE: 10302.53, MAPE: 11.55%
✅ Prophet Accuracy: 88.45%
```

Figure 11. Prophet model Evaluation & Accuracy

This code evaluates the Prophet model's forecast accuracy using MAE, RMSE, and MAPE by aligning predicted and actual sales data. With the lowest error values (MAE: 8337.36, RMSE: 10302.53, MAPE: 11.55%) and highest accuracy (88.45%), Prophet outperforms ARIMA, SARIMA, and LSTM, making it the most reliable model in this study.

V. CONCLUSION

This study conducted a comprehensive analysis of Amazon sales data from 2019 to 2024 using four time series forecasting models: ARIMA, SARIMA, LSTM, and Prophet. Each model was evaluated using standard performance metrics—MAE, RMSE, and MAPE—to determine forecasting accuracy.Prophet emerged as the top-performing model, delivering the most accurate results with the lowest MAE (8337.36), RMSE (10302.53), and MAPE (11.55%), translating to an overall accuracy of 88.45%.LSTM followed closely with competitive results, while SARIMA showed the weakest performance. These findings suggest that modern models like Prophet and LSTM, which effectively capture nonlinear trends and seasonality, are more suitable for retail sales forecasting. This insight can aid businesses in selecting the right predictive tools for inventory planning, sales strategy, and decision-making.

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