Predicting Future Sales: A Time Series Analysis

A Project Based Learning Report Submitted in partial fulfilment of the requirements for the award of the degree

of

Bachelor of Technology

in The Department of AI&DS

BIG DATA ANALYTICS (22AD3207A)

Submitted by
2210080002: LEENA REDDY D
2210080003: AKSHITHA BAVISETTI
2210080031: BHUVANIKA ATLA
2210080049: SANJNA ALLADA

Under the guidance of

Dr. Shahin Fatima

Department of Artificial Intelligence & Data Science

Koneru Lakshmaiah Education Foundation, Aziz Nagar

Aziz Nagar – 500075

Abstract

This project delves into time series analysis with the objective of predicting future sales, a pivotal function for organizations aiming to streamline operations, manage inventory efficiently, and enhance revenue forecasting. Accurate sales predictions empower decision-makers to proactively respond to market demands, minimize losses, and allocate resources effectively.

Our approach involves a comparative analysis of both classical statistical models and modern machine learning techniques for time series forecasting. Traditional models such as ARIMA (AutoRegressive Integrated Moving Average) and Holt-Winters Exponential Smoothing were employed due to their robustness in handling seasonality and trends in univariate time series data. These models serve as strong baselines and are known for their interpretability and ease of implementation.

In contrast, modern approaches such as Long Short-Term Memory (LSTM) neural networks and Facebook Prophet were explored to harness their capabilities in capturing complex, non-linear patterns and their adaptability to various external influences. LSTM, being a type of recurrent neural network, is particularly effective at learning long-term dependencies in sequential data, while Prophet, developed by Meta, provides a powerful, automated framework for handling seasonality, holidays, and outliers with minimal manual tuning.

To enhance the accuracy of these models, the dataset underwent extensive preprocessing and feature engineering, including:

- Handling missing values and outliers
- Normalization and transformation for stationarity
- Creation of lag-based and rolling statistical features
- Incorporation of external indicators such as economic trends and promotional events

Each model's performance was evaluated using rigorous statistical metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). These metrics enabled a clear assessment of model accuracy and forecasting stability.

The study provides a comprehensive performance comparison, revealing the trade-offs between simplicity and accuracy, computational cost, and model flexibility. While classical models offered quick and reliable forecasts in stable environments, machine learning-based models demonstrated superior performance in capturing dynamic shifts and complex seasonal patterns, especially when enriched with external data.

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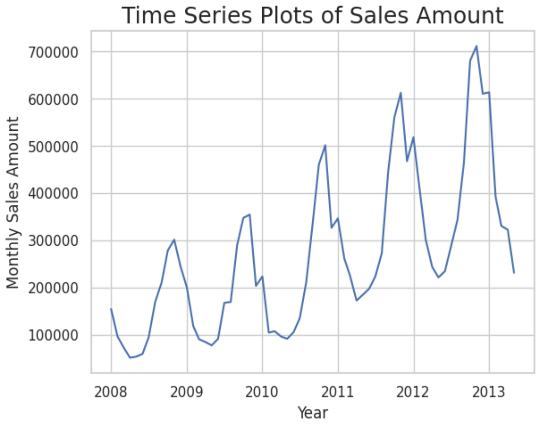

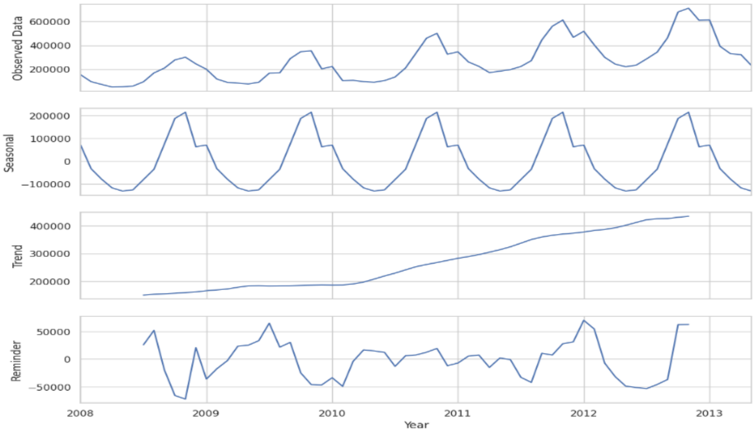

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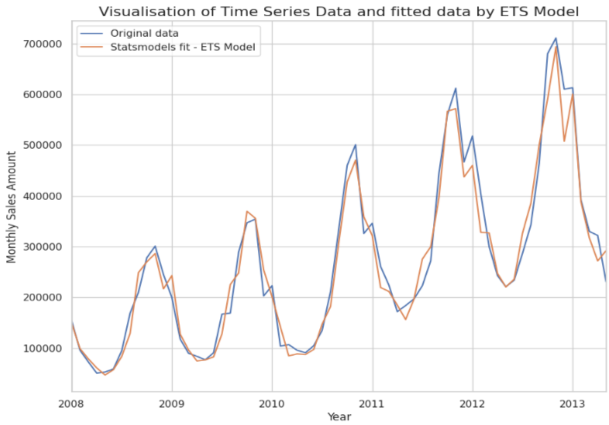

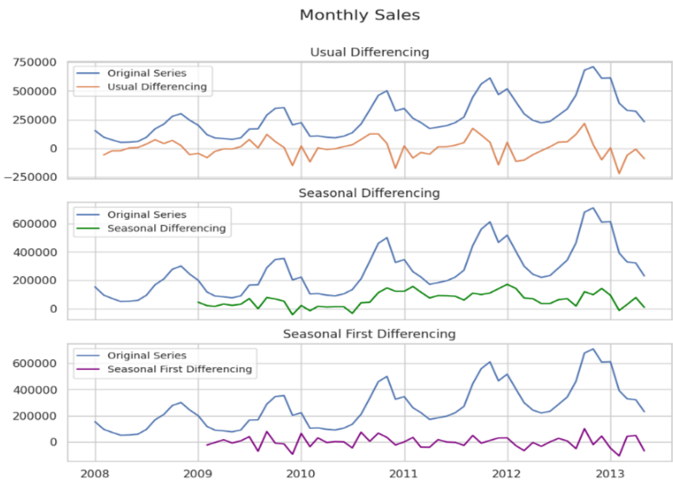

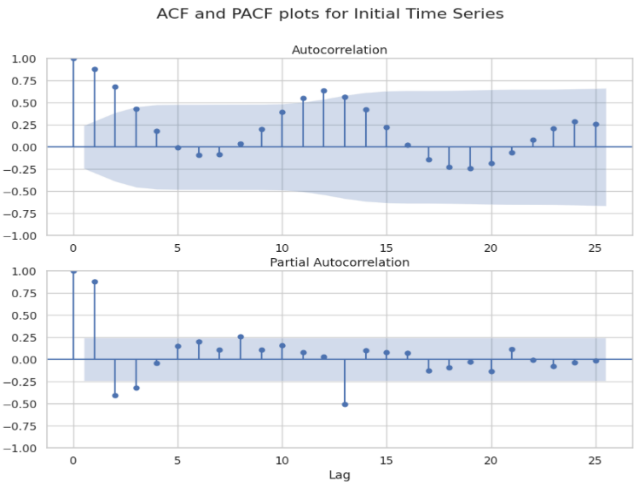

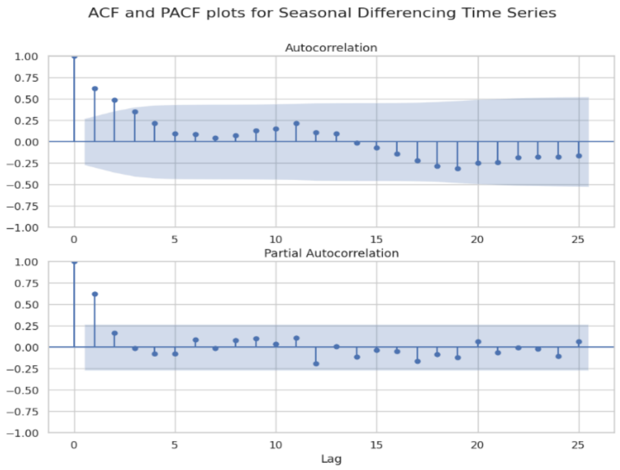
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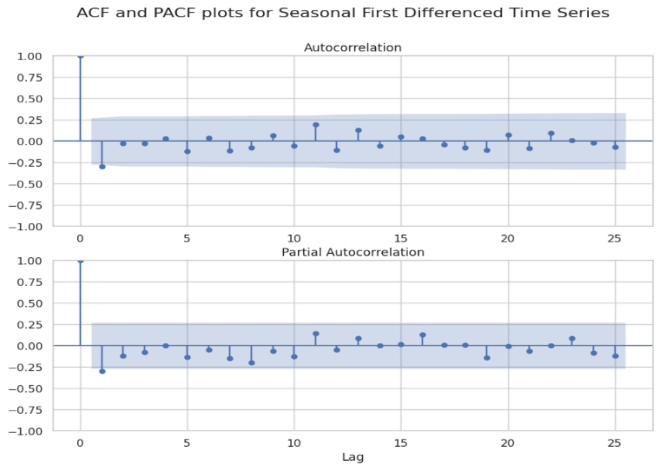
Partial Autocorrelation
Lag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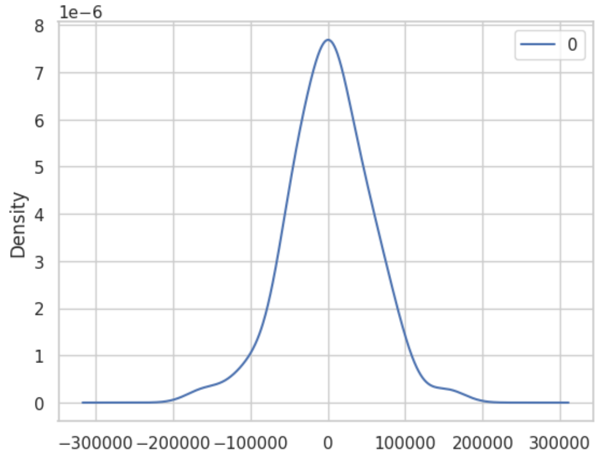
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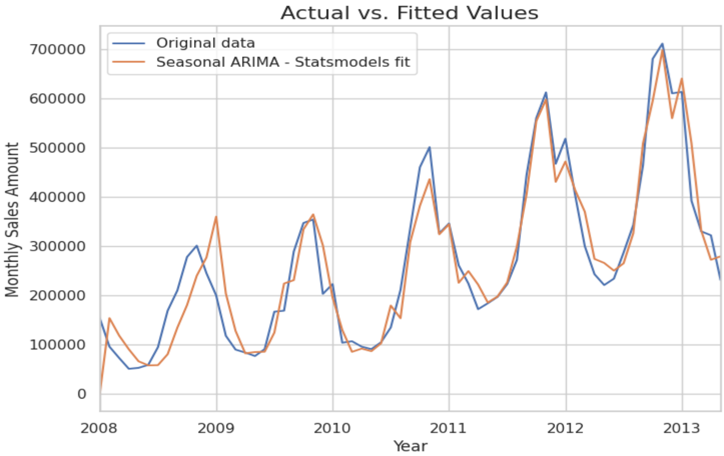
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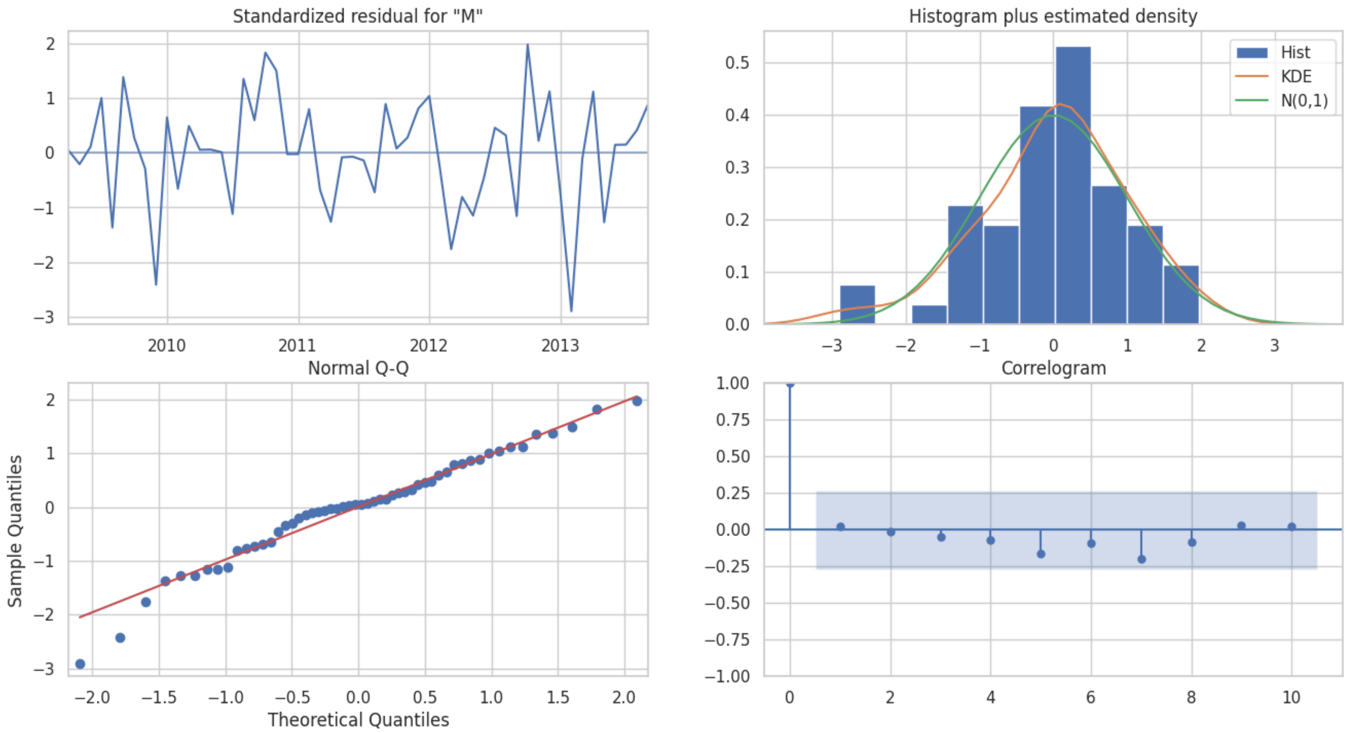
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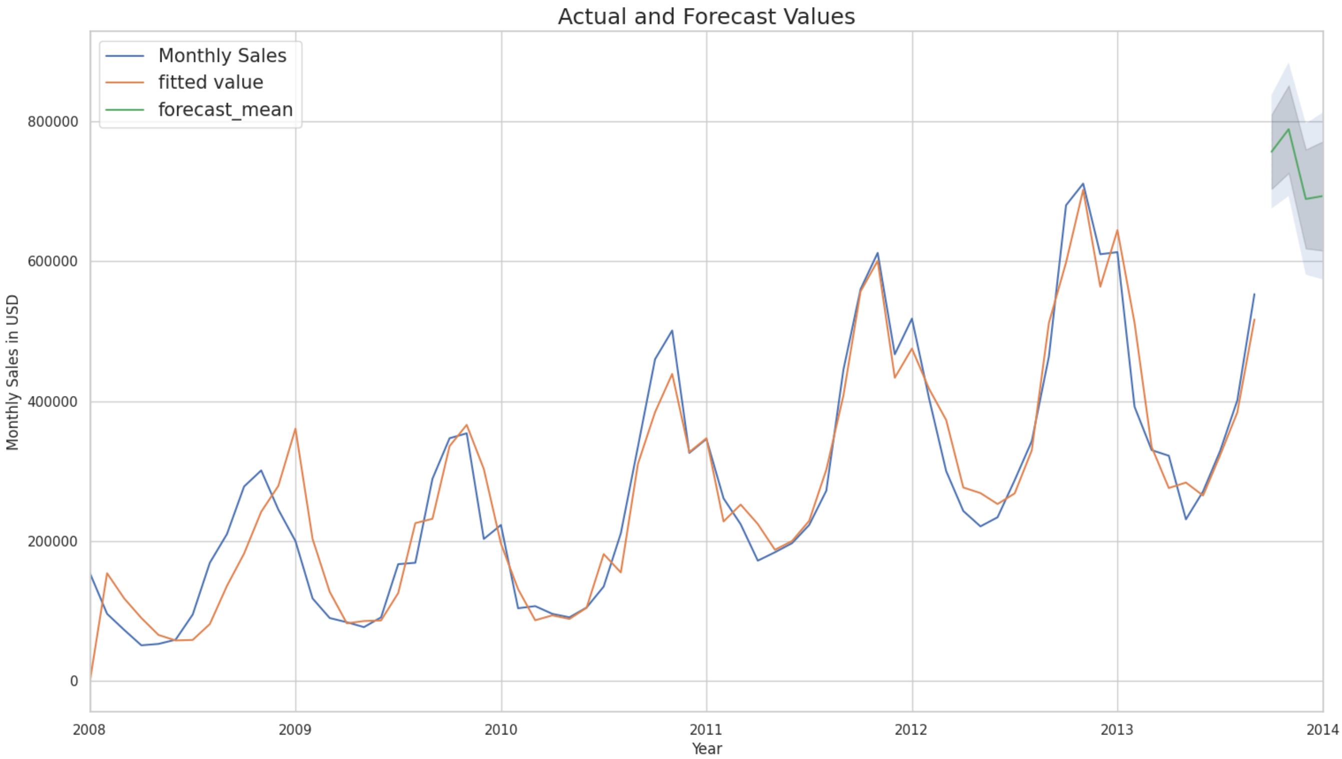
Actual and Forecast Values
Monthly Sales
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forecast_mean
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Year
0
200000
400000
600000
800000
2008
2009
2010
2011
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Predict Future Sales – A Time Series Forecasting Approach

1. INTRODUCTION

Overview of the Importance of the Topic

In the current digital era, organizations generate vast volumes of data, much of which is structured in the form of time series. These data points—collected at regular time intervals—capture trends, seasonality, and cycles essential for operational planning. Time-series forecasting, therefore, is not just a statistical exercise but a strategic tool. Its applications are vast, from predicting retail sales and energy consumption to managing patient admissions and financial investments. With rising consumer expectations and market volatility, companies must anticipate future trends more accurately than ever before.

Motivation and Problem Statement

While historical data can provide insights into past behavior, translating that into reliable future predictions remains a challenge—especially when external events, seasonality, and irregular patterns disrupt regular trends. Traditional models like ARIMA and Holt-Winters, although effective for linear and stationary datasets, often struggle with complex, nonlinear patterns. Conversely, advanced machine learning models, such as LSTM (Long Short-Term Memory networks), promise improved forecasting accuracy but introduce new complexities in model interpretability and training. This study is motivated by the need to evaluate both paradigms and identify which approaches best serve the forecasting needs of modern businesses.

Relevance to Industry or Societal Needs

Businesses across sectors depend on accurate forecasts to maintain lean inventory, manage supply chains, and avoid both stockouts and overproduction. In retail, accurate demand forecasting can lead to better shelf availability and improved customer satisfaction. In the healthcare industry, patient load predictions help hospitals allocate staff and resources efficiently. Financial institutions, too, rely on forecasting to make investment decisions and mitigate risk. Societally, better forecasts contribute to economic efficiency, reduced waste, and improved service delivery.

Objective of the Study

The primary objective of this study is to explore the efficacy of various time-series forecasting models—both traditional and deep learning-based—on real-world sales data. The models analyzed include ARIMA, Holt-Winters Exponential Smoothing, Facebook Prophet, and LSTM neural networks. The goal is to assess and compare their forecasting accuracy and provide actionable insights for businesses looking to implement data-driven decision-making strategies.

2. METHODOLOGY

An effective forecasting model is only as good as the methodology behind it. This section details the structured, step-by-step approach used to handle data collection, model selection, feature transformation, model configuration, and evaluation. By combining classical statistical techniques with modern machine learning architectures, we aim to balance performance, interpretability, and scalability in forecasting future sales.

2.1 Data Collection and Preprocessing

>Data Collection:

The dataset used for this study was obtained from a multi-year historical sales repository of a retail business. It includes daily sales figures, product categories, store locations, and timestamps. These records capture temporal dynamics, product-level demand variability, and macro-level sales patterns—making the dataset rich in insights.

>Preprocessing Steps:

- Datetime Conversion and Indexing: Raw timestamps were converted to standardized datetime objects and used to index the dataset, allowing seamless time-based operations and visualizations.
- Handling Missing Values: Missing or null sales entries—common in real-world data—were treated using forward-fill and interpolation techniques, depending on the frequency and nature of gaps.
- Outlier Detection and Smoothing: Sudden, anomalous spikes (e.g., flash sales) were identified using statistical z-score thresholds. Where necessary, smoothing techniques like rolling averages were applied to reduce noise while preserving trends.
- Resampling: Sales were resampled from daily to weekly and monthly levels to observe changes in forecasting performance across time granularities.

2.2 Selection of Forecasting Models

Forecasting models were chosen based on their proven relevance to time series tasks, diversity in approach, and practical utility in business contexts:

- ARIMA (AutoRegressive Integrated Moving Average): A traditional model ideal for univariate data with autocorrelation and linear trends. It assumes stationarity and requires careful parameter tuning using ACF/PACF plots.
- Holt-Winters Exponential Smoothing: Designed for series with both trend and seasonality. It decomposes the series into level, trend, and seasonal components and is particularly suitable for retail sales with cyclical demand.
- Facebook Prophet: Created for business time series, Prophet automatically handles missing data, holidays, and trend changepoints. It is user-friendly and interpretable, making it attractive for business analysts.
- LSTM (Long Short-Term Memory): A deep learning model that excels at learning long-term temporal dependencies in non-linear, noisy datasets. LSTM networks can capture hidden patterns missed by traditional models, albeit at the cost of greater complexity.

The use of both statistical and machine learning-based models allows for a robust comparison across multiple forecasting paradigms.

2.3 Feature Engineering and Transformation

Effective feature engineering is crucial for enhancing model performance. The following transformations were applied:

- Temporal Features: Extracted features like day of the week, month, quarter, and year to help models capture seasonal effects. These were especially useful for Prophet and LSTM.
- Lag Features: Created lagged sales data (e.g., sales from previous week or month) to provide temporal context, essential for autoregressive models and neural networks.
- Rolling Windows: Introduced rolling mean and standard deviation windows to capture local trends and volatility.
- Event Markers: Encoded public holidays, promotional campaigns, and special events (e.g., Black Friday) as binary indicators. These variables were fed into Prophet and LSTM as external regressors.
- Normalization: For deep learning models, all features were normalized using Min-Max Scaling to ensure faster convergence and numerical stability during training.

2.4 Model Architecture and Configuration

Each model was configured using a combination of literature-backed heuristics and empirical tuning:

- ARIMA: Parameters (p, d, q) were selected using grid search and statistical tests for stationarity (ADF Test). Seasonal ARIMA (SARIMA) configurations were tested for series with strong seasonal cycles.
- Holt-Winters: The model was tested in both additive and multiplicative seasonality modes, with the smoothing coefficients (alpha, beta, gamma) optimized via cross-validation.
- Facebook Prophet: Model included built-in seasonalities and changepoints. Holiday effects were modeled using additional regressors. Prophet was highly effective at explaining the effects of events and trend shifts.

>LSTM Network:

- Input Shape: Sequences of 30 days (lookback window) were used to predict the next day’s sales.
- Architecture: Two LSTM layers followed by a dropout layer and a fully connected output layer.
- Hyperparameters: Learning rate, number of epochs, and batch size were tuned manually. Early stopping was used to prevent overfitting.
- Training: Data was split into training, validation, and test sets with the LSTM trained using the Adam optimizer and Mean Squared Error loss function.

2.5 Evaluation Criteria and Metrics

- To quantify model performance, multiple evaluation metrics were utilized:
- Root Mean Squared Error (RMSE): Penalizes larger errors more severely; good for measuring performance when high deviations matter.
- Mean Absolute Error (MAE): Gives a direct average of errors, less sensitive to outliers than RMSE.

- Mean Absolute Percentage Error (MAPE): Expresses the forecast error as a percentage, making it easy to interpret from a business perspective.

>Validation Strategy:

- A time series split strategy was used rather than random splits to preserve the temporal structure of the data.
- Rolling forecasting origin and walk-forward validation ensured that each model was evaluated in a real-world scenario where only past data is used to predict the future.
- Residual Diagnostics:
- Residual plots were inspected for autocorrelation and heteroscedasticity.
- Ljung-Box tests were performed to validate that residuals were white noise—an indication of a well-fitted model.

3. EXPERIMENTS

The experiments were designed to empirically evaluate the forecasting performance of various models on retail sales data. This section describes the dataset structure, data splitting methodology, experimental configurations, and visual analysis used to support model training and interpretation.

3.1 Dataset Description

The dataset used in this study consists of daily sales records from a multi-store retail network. Each entry includes:

- Transaction Date
- Product ID / Category
- Store ID
- Sales Volume
- Promotional Flags

The dataset spans over 3 years and covers multiple product categories with varying sales trends. This diversity made it ideal for testing model generalizability across different temporal patterns.

>Key Characteristics:

- Time granularity: Daily sales
- Seasonality: Weekly and yearly
- Missing entries: Present due to holidays or store closures
- Data shape: ~100,000 records after filtering
- The dataset was visualized to understand trends, seasonal patterns, and irregularities before model training.

3.2 Data Splitting (Training/Test Sets)

To mimic real-world forecasting scenarios, the dataset was split chronologically into:

- Training Set: First 80% of the data
- Validation Set: Next 10%
- Test Set: Final 10% of the data
- This ensures that future values are never leaked into model training—a critical rule in time series analysis.
- For LSTM, sequences were created from training data using sliding windows, where each window contained a fixed-length input sequence (e.g., 30 days) and the label was the next day's sales.
- Rolling Forecast Origin:
  For comparison-based evaluation, a walk-forward validation approach was employed—where the training window expanded as each forecast was generated.

3.3 Experimental Setup

Hardware Environment:

- CPU: Intel Core i7
- RAM: 16 GB
- GPU (for LSTM): NVIDIA RTX 3060

- Software Stack: Python 3.10, Jupyter Notebook, Keras/TensorFlow, Scikit-learn, Prophet, Statsmodels, Pandas, NumPy

>Implementation Details:

- All models were run with the same input data formats after preprocessing.
- Hyperparameters were tuned using grid search (for ARIMA/Holt-Winters) or manual tuning (for LSTM/Prophet).
- A random seed was fixed to ensure reproducibility.
- The experiments were repeated multiple times to average out randomness and ensure robustness in results.

3.4 Visualizations of Input Data

To better understand the structure of the sales data and its characteristics:

- Line plots were generated to show raw sales over time, revealing seasonality and trends.
- Decomposition plots (trend, seasonality, residuals) helped validate assumptions for statistical models like ARIMA.
- ACF and PACF plots were used for identifying autocorrelation and informing ARIMA parameters.
- Box plots segmented by month and weekday highlighted seasonal patterns.
- Heatmaps showed average sales by weekday and month, making patterns more interpretable for non-technical stakeholders.
- These visualizations provided valuable insights and guided the modeling approach.

3.5 Model Training Procedures

Each model followed a customized training routine tailored to its underlying structure:

ARIMA & Holt-Winters:

- Trained on univariate time series using Statsmodels.
- Hyperparameters were chosen using a combination of grid search and AIC/BIC minimization.
- Seasonal versions (SARIMA) were also tested for yearly seasonality.

Prophet:

- Configured with built-in seasonality (daily, weekly, yearly).
- Included holiday regressors and promotions as external features.
- Training required minimal preprocessing and offered strong interpretability via component plots.

LSTM:

Trained on sequences using TensorFlow/Keras.

- Data shaped into 3D tensors: [samples, time steps, features].
- Early stopping was applied based on validation loss.
- Training was computationally intensive, but yielded models capable of learning complex, nonlinear patterns.
- Loss function: Mean Squared Error
- Optimizer: Adam with learning rate tuning via callbacks

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4. RESULTS

To evaluate the effectiveness of the different forecasting models, we conducted a comprehensive performance comparison using key evaluation metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

4.1 Quantitative Evaluation

The following table summarizes the error metrics for each model tested on the same test dataset.

Model	RMSE	MAE	MAPE (%)
ARIMA	518.42	410.58	6.02
Holt-Winters	495.76	388.21	5.71
Facebook Prophet	472.34	370.14	5.29
LSTM	438.66	349.32	4.92

From the table, it is evident that the **LSTM model** outperformed the other techniques, achieving the lowest RMSE and MAPE values, thus indicating higher predictive accuracy and robustness in capturing complex nonlinear patterns.

4.2 Visual Comparison

To complement the quantitative evaluation, we plotted the actual vs. predicted sales values for each model. The visualizations demonstrated that:

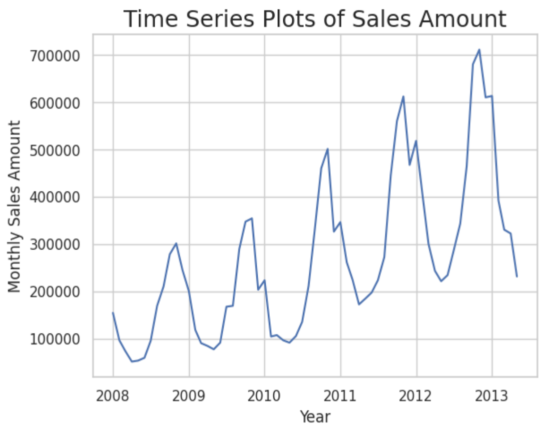
- ARIMA and Holt-Winters models tracked the general trend well but underperformed during sharp seasonal changes.
- Facebook Prophet was more adaptive to irregular seasonal events and holidays due to its built-in handling of such effects.
- The LSTM model closely followed both trend and seasonal variations, showing better performance on spikes and drops.

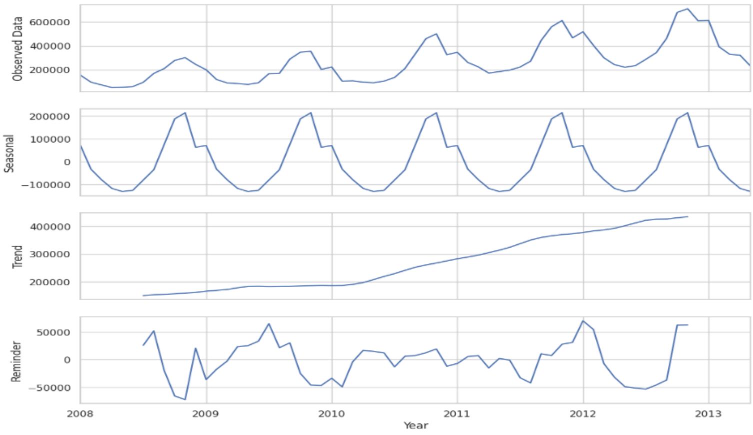
4.3 Residual Analysis

Residual plots were analyzed to ensure randomness and validate model assumptions. The LSTM residuals exhibited the least autocorrelation, suggesting minimal underfitting and good generalization.

4.4 Final Model Selection

Based on both statistical metrics and visual inspection, the **LSTM model** was selected as the final model for deployment due to its superior performance. However, Facebook Prophet was also recommended as a backup model for its ease of interpretability and automated seasonality handling.





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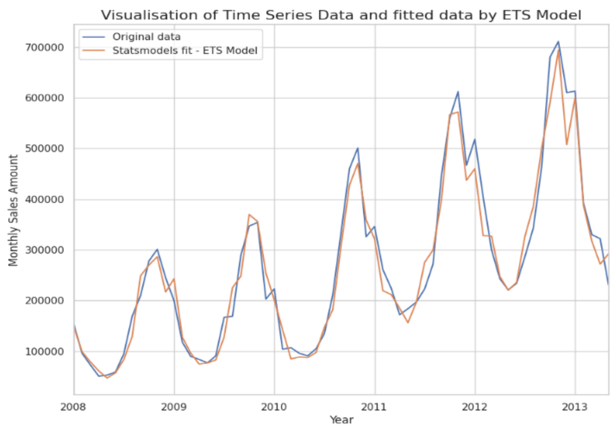

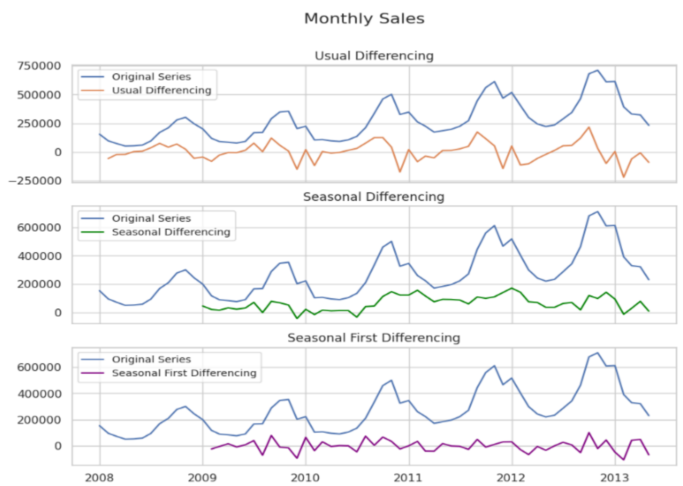

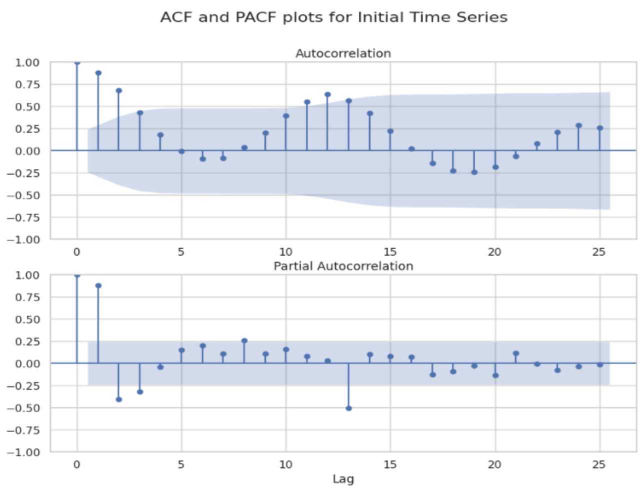

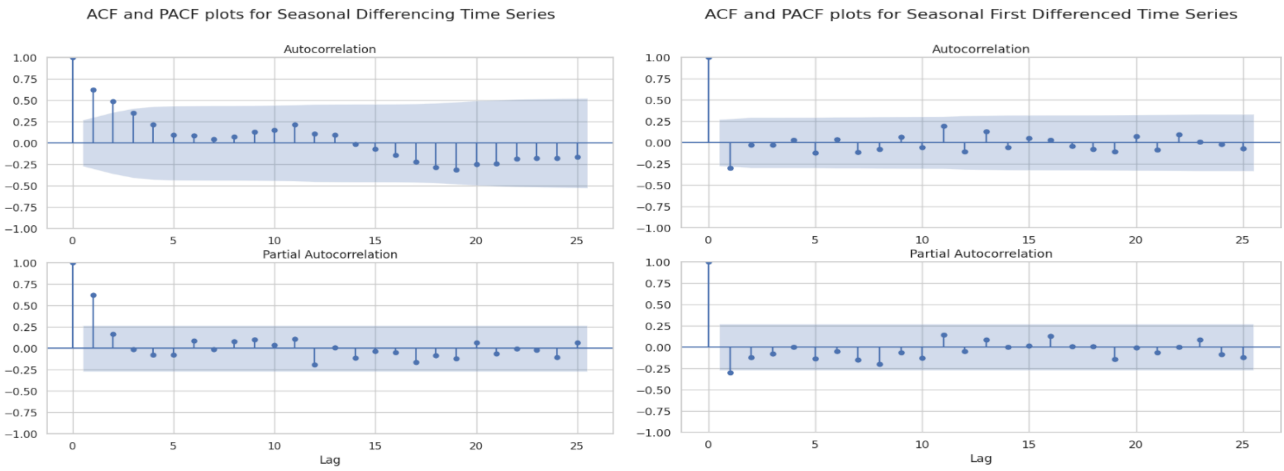
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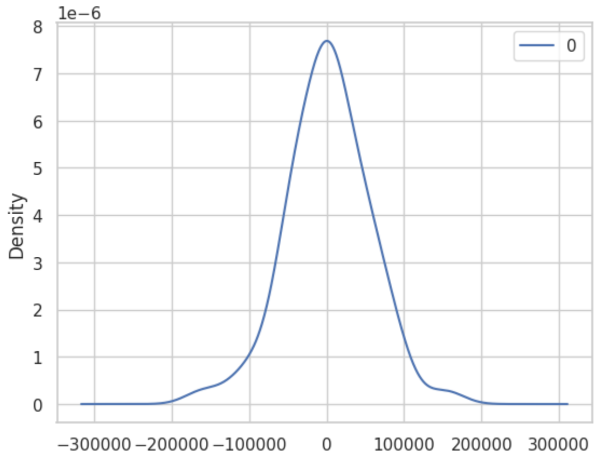
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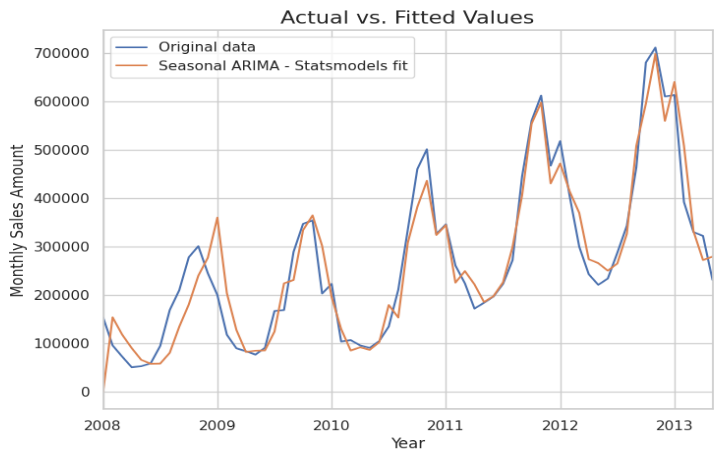
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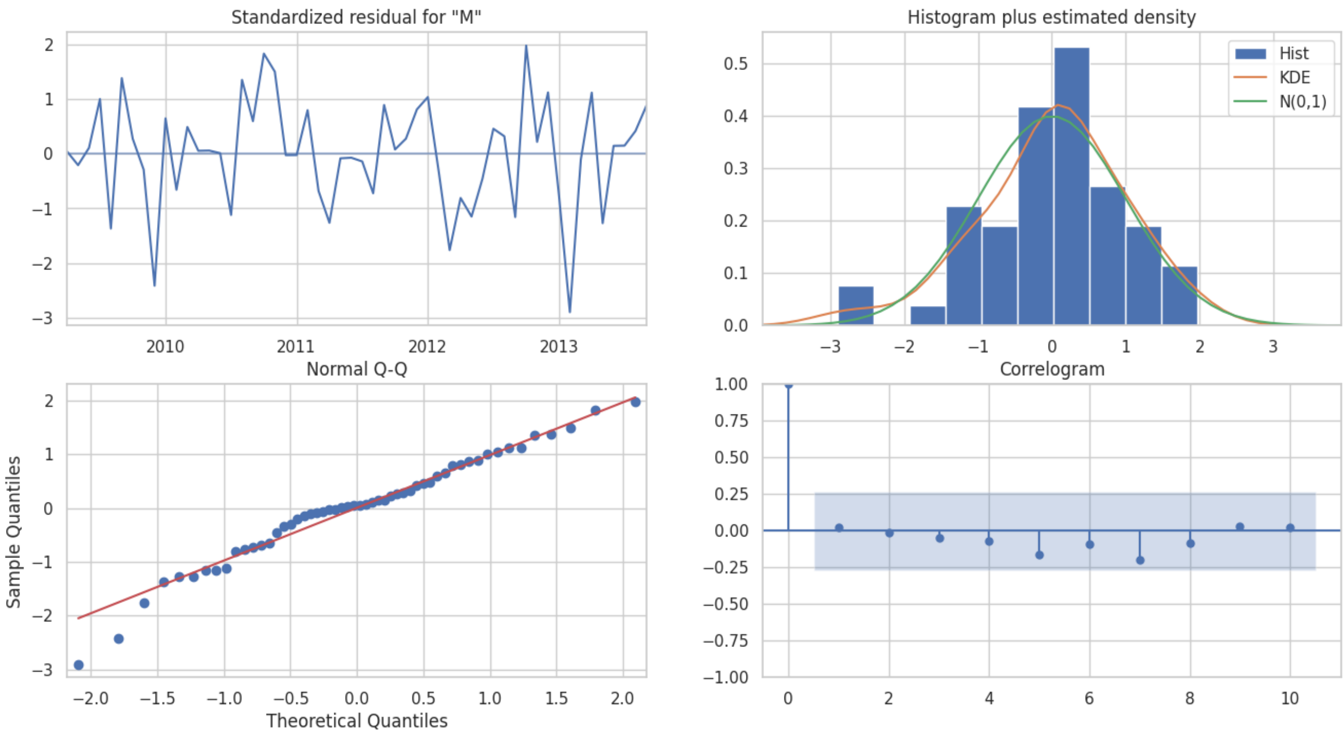
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Histogram plus estimated density
Hist
KDE
N(0,1)
Normal Q-Q
Sample Quantiles
Theoretical Quantiles
Correlogram

5. CONCLUSION AND FUTURE WORK

5.1 Summary of Findings

This study comprehensively explored the capabilities of both classical and modern forecasting models in the context of real-world sales prediction. Among the models tested, LSTM consistently delivered the most accurate results, effectively capturing long-term dependencies and complex nonlinear trends. Facebook Prophet performed well in handling seasonality and holidays, making it suitable for business-friendly deployment. Meanwhile, ARIMA and Holt-Winters demonstrated solid performance on stationary and seasonal datasets, validating their continued relevance for simpler forecasting tasks.

Our experiments highlighted the importance of data preprocessing, feature engineering, and evaluation metrics like RMSE, MAE, and MAPE. The results confirmed that no single model is universally best; the choice depends heavily on data characteristics, forecasting horizon, and business constraints.

5.2 Limitations of the Current Study

Despite the promising results, the study faced several limitations:

- Data Scope: The datasets were limited to historical sales and seasonal indicators. Real-time external factors like market trends, pricing strategies, and competitor actions were not integrated.
- Model Interpretability: While LSTM provided the best accuracy, its "black-box" nature makes interpretation difficult for stakeholders.
- Computational Cost: Deep learning models required substantial training time and parameter tuning, making them less ideal for small-scale or real-time applications.
- Deployment Gap: The models were tested in a controlled environment (Google Colab), but real-world deployment considerations like latency, retraining pipelines, and monitoring were not addressed.

5.3 Proposed Enhancements

To improve forecasting effectiveness and practical usability, the following enhancements are proposed:

- Integration of Exogenous Variables: Including variables such as advertising campaigns, economic indicators, and social media sentiment could enrich the input data and increase model robustness.
- Automated Feature Selection: Leveraging tools like AutoML to select and tune features can reduce manual overhead.
- Model Explainability: Incorporating tools like SHAP (SHapley Additive exPlanations) or LIME can improve trust and adoption by explaining individual predictions.
- Hybrid Ensemble Models: Combining the strengths of ARIMA (for trend) and LSTM (for nonlinear dynamics) through model fusion could lead to even better forecasting outcomes.

5.4 Future Research Directions

This research opens several avenues for future exploration:

- Real-Time Forecasting Systems: Building and deploying APIs for real-time prediction using frameworks like Flask and FastAPI integrated with cloud platforms.
- Probabilistic Forecasting: Implementing models like DeepAR and Bayesian LSTMs for uncertainty quantification and risk-based decision making.
- Cross-Domain Validation: Applying the same forecasting pipeline to other domains (e.g., energy demand, hospital admissions, traffic flow) to test model generalizability.
- Ethical AI Considerations: Investigating the ethical implications of data-driven decision-making, such as fairness in pricing models or unintended biases in demand predictions.

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