CS-6010: Final Project
SALES FORECASTING PREDICTION

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Abstract

This report presents a sales forecasting project that uses time series analysis of machine learning algorithms. The challenge is to build an accurate model using historical data and relevant features. The project will use publicly available data and algorithms such as Seasonal Naive, Holt-Winters, ARIMA, Linear Regression, Random Forest, XGBoost, and LSTM networks. The algorithms will be customized and improved with feature engineering, hyperparameter refinement, and possibly ensemble techniques or advanced preprocessing methods. The project will undergo qualitative and quantitative evaluations to ensure reliable and accurate sales forecasts, helping businesses optimize their strategies and operations.

1. Introduction

This report presents a comprehensive sales forecasting project that utilizes the power of time series analysis and advanced machine learning techniques. In today's highly competitive business environment, accurately predicting future sales is not only advantageous but also essential. Sales forecasting plays a crucial role in strategic decision-making, allowing businesses to optimize inventory management, allocate resources efficiently, and plan future growth strategies. The project's objective is to develop a robust and accurate forecasting model that combines historical sales data with relevant market indicators.

The main focus of this project is to use different forecasting algorithms such as Seasonal Naive, Holt-Winters, ARIMA, Linear Regression, Random Forest, XGBoost, and LSTM networks. Each algorithm has its own strengths, and the selection of algorithm depends on the specific attributes of the dataset. The project goes beyond the application of standard models by customizing and improving these algorithms. This customization process involves intricate feature engineering, hyperparameter optimization, and possibly using advanced preprocessing methods or ensemble techniques to enhance the model's performance.

The project uses rigorous evaluation methods, such as visual assessments and metrics like MAE and RMSE, to ensure accurate sales forecasts. It aims to provide valuable insights to businesses for informed decision-making in a dynamic market.

2. Related Work

2.1 Application of Deep Learning Models in Sales Forecasting:

This study aimed to improve sales forecasting using deep learning models like LSTM (Long Short-Term Memory) networks. The focus was on the model's ability to capture complex patterns in time series data. Our approach stands out by integrating a wider range of algorithms, including both traditional machine learning models and deep learning techniques. This provides a more comprehensive analysis, making our method more flexible and adaptable to different types of data. As a result, it has the potential to generate more accurate predictions across various contexts.[1]

2.2 Enhancing Sales Forecast Accuracy with XGBoost:

This research focused on using the XGBoost algorithm to efficiently handle large datasets and analyze feature importance for sales forecasting. In addition to XGBoost, our project also utilized other algorithms and feature engineering techniques to optimize performance. By using a multi-model approach, we aim to leverage the strengths of different algorithms and reduce the weaknesses of individual models, potentially resulting in better results.[2]

2.3 Integrating ARIMA with Machine Learning for Sales Prediction:

This work investigates the integration of ARIMA, a conventional time series analysis method, with advanced machine learning techniques to improve the accuracy of predictions. Our project builds on this integration by incorporating more advanced machine learning models and a comprehensive evaluation process. Our approach is expected to provide a more robust solution by balancing the advantages of classical statistical methods and modern machine learning techniques.[3]

3. Problem Definition

3.1 Task Definition

The problem addressed in this report is the precise pre-

diction of future sales for businesses using historical sales data and relevant market indicators. The primary inputs for this problem include historical sales figures, which may encompass various timeframes (daily, weekly, monthly, yearly), and potentially other relevant data such as economic indicators, market trends, fuel price, and Temperature effect. The desired output of this model is a set of predicted sales figures, which can be compared with actual sales.

Accurate sales forecasting is crucial for businesses to anticipate market demands, manage inventory efficiently, allocate resources wisely, and plan strategically. This project uses advanced machine learning techniques to transform data into meaningful insights, enabling businesses to make informed decisions and plan strategically for enhanced accuracy and profitability.

4. Algorithm Definition

4.1 ARIMA model

The ARIMA model, or Autoregressive Integrated Moving Average, is a widely used statistical approach for time series forecasting. ARIMA models are particularly suitable for short-term forecasting where the data show evidence of non-stationarity, and one or more of the time series' statistical properties change over time. I am using the **pmdarima** library in Python for ARIMA modeling. This library simplifies the process of identifying the most suitable ARIMA model for time series data.
ARIMA combines three key components: AutoRegression (AR), Integration (I), and Moving Average (MA).

AutoRegression (AR): This part of the model exploits the relationship between an observation and a number of lagged observations (past values).

Integration (I): This component is used to make the time series stationary by differencing the data (subtracting an observation from an observation at the previous time step).

Moving Average (MA): This part models the error of the model as a combination of past errors.

The ARIMA model is often denoted as ARIMA(p, d, q), where 'p' is the number of lag observations, 'd' is the degree of differencing, and 'q' is the size of the moving average window.

Pseudocode for ARIMA:
1. Choose p, d, and q based on data characteristics.
2. Differencing the data d times to make it stationary.
3. Fit the ARIMA model to the data:
- Use p past values for AR part.
- Use q past forecast errors for MA part.
4. Forecast future values.

Example:
Consider a simple time series: [110, 120, 130, 120, 140]. Assume we choose an ARIMA(1, 1, 1) model.

Differencing: The first difference of the series is [10, 10, -10, 20].
Model Fitting:
AR(1): Model the next value as a function of the previous value (e.g., 120 is modeled based on 110).
MA(1): Model the next value using the previous error (e.g., the error in predicting 120 based on 110).
Forecasting: Use the fitted model to forecast future points in the series.

In this example, the ARIMA model would use the most recent data point and the most recent error to forecast the next point in the series. The simplicity of this example illustrates the core principles of ARIMA modeling, even though real-world applications typically involve more complex data and parameter selections.

4.2 Holt-Winters

The Holt-Winters algorithm, also known as the Triple Exponential Smoothing method, is a popular and effective technique for time series forecasting, especially for data with seasonal patterns. It extends the classical exponential smoothing approach by adding two more components: a trend component and a seasonal component.

Level: Estimates the current value of the series.

Trend: Captures any systematic trend in the series.

Seasonality: Accounts for seasonal variations.

Pseudocode for Holt-Winters:
1. Initialize level, trend, and seasonal components.
2. For each time step in the series:
a. Update the level component (Alpha).
b. Update the trend component (beta).
c. Update the seasonal component (Gama).
d. Forecast = Level + Trend + Seasonality.
3. Repeat for the desired forecasting period.

Example:
Consider a monthly sales dataset with a clear annual seasonal pattern.
Initialization: Start with initial estimates for level, trend, and seasonality (these might be the first data point, the initial trend, and the initial seasonal indices).
Update Steps:

1. Update the level based on the current data point, considering the previous level and trend.

2. Update the trend based on the change in level.

3. Update the seasonal component based on the current seasonality.

4. Produce the forecast for the next period as the sum of the updated level, trend, and seasonal components.
This example shows how the Holt-Winters algorithm

forecasts time series data by adapting to changes in level, trend, and seasonality.

4.3 Linear Regression

The Linear Regression algorithm is a foundational technique in statistical modeling and machine learning, used for predicting a continuous dependent variable based on one or more independent variables. It assumes a linear relationship between the input variables (predictors) and the single output variable (response). The goal is to find the best-fitting straight line through the data points.

Pseudocode for Linear Regression:

1. Start with a set of data points (xi, yi).

2. Initialize coefficients (slope and intercept).

3. Calculate the predicted values (ypred) using the linear equation.

4. Compute the cost (sum of squared differences between ypred and actual y).

5. Adjust the coefficients to minimize the cost.

6. Repeat steps 3-5 until convergence or a maximum number of iterations is reached.

Example:

Consider a dataset with the following points that represent sales (y) based on advertising spend (x): (1, 2), (2, 3), (3, 5), (4, 4).

To start, make initial guesses for the slope (m) and intercept (c).

Next, predict the sales for each advertising spend using the initial guesses. Then, calculate the cost by adding up the squared differences between the predicted sales and the actual sales.

After that, adjust the values of m and c to reduce the cost. This is usually accomplished using gradient descent or another optimization technique.

Repeat the prediction and adjustment steps until the model converges to the minimum cost.

In this example, Linear Regression would try to find the line that best represents the relationship between advertising spend and sales.

4.4 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) used for modeling sequential data, particularly effective in capturing long-term dependencies in time series data like sales. LSTMs are designed to overcome the limitations of traditional RNNs, particularly issues related to long-term dependencies.

LSTMs maintain a cell state and utilize gates (input, output, and forget gates) to regulate the flow of information. These gates determine what information should be retained or discarded throughout the sequence of data, enabling the network to make more accurate predictions based on long-term patterns.

Pseudocode for LSTM:

1. Preprocess Data: Scale numeric features, encode categorical variables.

2. Build LSTM Model: Use layers like LSTM cells in TensorFlow/Keras.

3. Train Model: Fit the model to training data using sequences.

4. Evaluate Model: Use metrics to assess performance.

5. Predict: Make predictions on test data.

6. Visualize: Compare actual vs. predicted sales.

Example:

To predict sales for upcoming months using monthly sales data over two years, the following steps can be taken:

1. Preprocess sales data by normalizing and structuring it into monthly sequences.

2. Build an appropriate LSTM model.

3. Train the model using historical sales data.

4. Evaluate the model using RMSE.

5. Use the model to forecast future sales.

6. Visualize the accuracy of the model by plotting actual sales against forecasted sales.

In this example, the LSTM network would learn from the patterns in the historical sales data, taking into account long-term trends and seasonal variations, to make predictions about future sales. This ability to recognize and remember long-term patterns makes LSTM particularly suitable for time series forecasting like sales data.

4.5 Random Forest

Random Forest is a versatile and robust machine-learning algorithm used for both classification and regression tasks. It operates by constructing multiple decision trees during training and outputting the mean prediction of the individual trees for regression tasks, or the mode of the classes for classification tasks.

Random Forest builds numerous decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control overfitting. The fundamental concept is that a group of weak models (decision

trees) can collectively form a strong model.

Pseudocode for Random Forest:

1. Select N random subsets from the training data.

2. For each subset:
a. Build a decision tree.
b. At each node, randomly select a subset of features and determine the best split.

3. To make a prediction:
a. Aggregate predictions from all the N trees.
b. For regression, take the average of these predictions.

Example:
Consider a dataset with features like store location, day of the week, and marketing spend, and the target variable is daily sales.
Building Trees: Random Forest selects random subsets of the data and builds decision trees on each subset. In each tree, at every decision node, a random subset of features (e.g., store location, day of the week) is considered for splitting.

Making Predictions: For predicting the sales on a particular day, each tree in the forest makes a prediction. The final output of the Random Forest model is the average of all these tree predictions.

This approach ensures that the Random Forest model captures various aspects and patterns in the data, leading to a robust and well-generalized model for predicting sales.

4.6 XGBoost

XGBoost (eXtreme Gradient Boosting) is an advanced implementation of gradient boosting algorithms. It has gained popularity due to its efficiency, speed, and performance in machine learning competitions. XGBoost works by sequentially adding predictors (trees), where each new predictor corrects its predecessor's errors. Unlike random forests, which build each tree independently, gradient boosting builds one tree at a time.

XGBoost uses a gradient descent algorithm to minimize errors in sequential models. It involves creating and adding trees to the model, where each new tree helps in correcting errors made by the previous ones. XGBoost also includes regularization terms in its objective function to prevent overfitting, making it effective for high-dimensional data.

Pseudocode for XGBoost:

1. Initialize the model with a single tree.

2. For each iteration:
a. Build a new tree that predicts the residuals or errors of the previous tree.
b. Add this tree to the model with an optimal weight.
c. Update the model to minimize the loss function (using gradient descent).

3. Repeat until a specified number of trees are added or no further improvements can be made.

Example:
Consider a dataset for predicting house prices based on features like size, location, and age.

Initial Model: Start with a simple model (a single tree).

Iterative Improvement:
The next tree in the sequence focuses on the errors (differences between actual and predicted prices) made by the first tree.
Each successive tree works on correcting the residual errors of the combined preceding trees.

Final Prediction: The output for a given house's price is the sum of predictions from all trees.

XGBoost's strength lies in its ability to sequentially improve predictions, making it highly effective for complex regression and classification problems.

5. Experimental Evaluation

5.1 Methodology

The methodology of this project involves a comprehensive approach to evaluating and testing various machine learning and statistical models for sales forecasting. The primary focus is on utilizing historical sales data and relevant market indicators to predict future sales accurately.

Evaluation Criteria:
Evaluation criteria are used to assess the effectiveness of different methods. Some of the primary criteria used in this evaluation are accuracy, robustness, computational efficiency, and scalability. Accuracy is measured using metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Symmetric Mean Absolute Percentage Error (sMAPE). Robustness refers to the ability of the method to handle various market conditions and data variability. Computational efficiency measures the time and resources required to train and run the models, whereas scalability looks at how well the model performs as the data size increases.

Hypotheses:
The experiment conducted in this project tests two specific hypotheses related to sales forecasting:

Hypothesis 1 (H1): Advanced machine learning models (like XGBoost, Random Forest, LSTM) provide more accurate forecasts than traditional statistical methods (such as ARIMA, Holt-Winters). This hypothesis posits that the incorporation of modern machine learning techniques,

which are capable of handling complex patterns and large datasets, will result in more precise sales predictions compared to classical time series analysis methods.

Hypothesis 2 (H2): Ensemble methods and hybrid models enhance prediction accuracy compared to single-model approaches. This hypothesis suggests that combining multiple models or employing hybrid approaches, which leverage the strengths of different algorithms, will lead to improved accuracy in forecasting sales. The rationale is that ensemble methods can capture a broader range of patterns and reduce the likelihood of overfitting, leading to more reliable predictions.

Experimental Methodology:
The experimental methodology used in project, involves several stages:

1. Data Collection: The Walmart datasets are sourced from the Kaggle platform and include 4 CSV files. There are several datasets available, including the Features dataset, which has 8191 rows and 12 columns, including information on the number of stores, sales date, temperature, fuel prices, and whether or not it is a holiday. The Stores dataset includes information on 45 stores, including their type and size. The Train dataset has 421571 rows and 5 columns, including data on the stores, department (1-98), weekly sales, date, and whether or not it is a holiday. Lastly, the Test dataset contains 115065 rows and 4 columns, including information on the store, department, date, and isholiday.

2. Data Preprocessing: During this phase, By replacing the missing values in the 'CPI' and 'Unemployment' columns with their respective medians, we have ensured that our data is more accurate and reliable than ever before. Additionally, we have taken care of negative and missing values in the 'MarkDown' columns by replacing them with zeros. We have merged various datasets and eliminated duplicated columns, making our data more organized and easier to manage. To make our data even more accessible, we have converted the 'Date' column to 'Datetime' format. All of these steps have culminated in the creation of a cleaner, more usable dataset, which we have saved as 'Cleandata.csv'.

3. Exploratory Data Analysis (EDA): Post-preprocessing, an extensive EDA was conducted. This involved utilizing various visualization techniques to uncover underlying patterns and insights within the data. To achieve this, we need to get a sense of your data distribution, including the mean, median, and other relevant measures. We identify the best months and years for sales by visualizing the data.

But that's not all. To gain a deeper understanding of Walmart's weekly sales by store type across different months and years, we created line plots and bar graphs. Additionally, we use plots like time series and histograms to detect patterns and trends in the data.

Finally, we conduct a correlation analysis to identify the relationships between different variables. So, that we can gain a comprehensive understanding of data and make informed decisions that will drive our success.

Key Findings:

- The sales data is not available for the last two months of 2012 (Figure 1).

- November and December had higher sales compared to the other months (Figure 2).

- The top 5 sales averages per week were observed during the 1-2 weeks before Christmas, Thanksgiving, and Black Friday (Figure 4).

- The 47th and 51st weeks had significantly higher averages (Figure 5).

- There are 45 stores and 81 departments, but the departments vary by store.

- Sales were highest in 2010 compared to 2011 and 2012.

- The unemployment rate has been decreasing over time, while the overall Consumer Price Index (CPI) has been increasing.

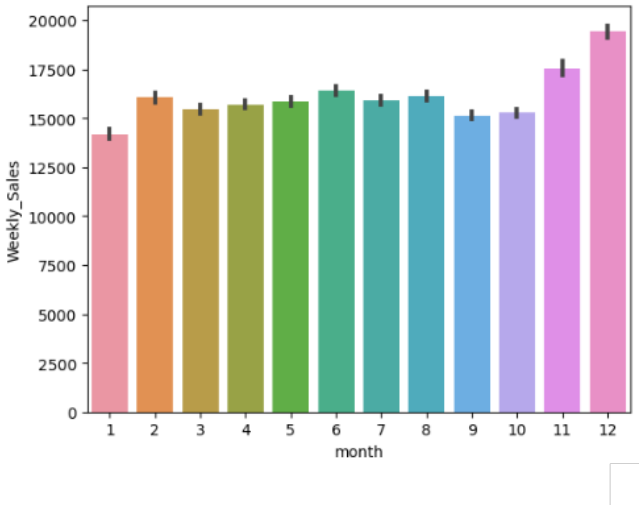

Figure 1: Weekly Sales for 12 Months

4. Feature Engineering: I first converted the 'Date' column into a datetime object and then extracted the year, month, and day as separate features. To avoid redundancy in the dataset, I dropped the original 'Date' column. Next, I transformed the 'Type' categorical variable into numerical format using label encoding. I also created new features by combining existing ones, namely 'StoreDept' and

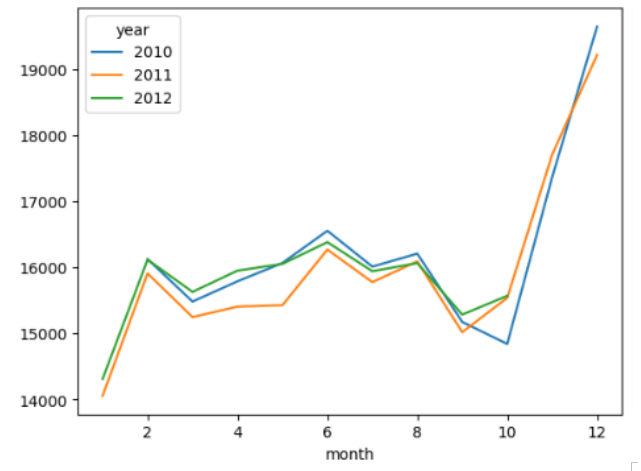

Figure 2: monthly sales for all 3 years

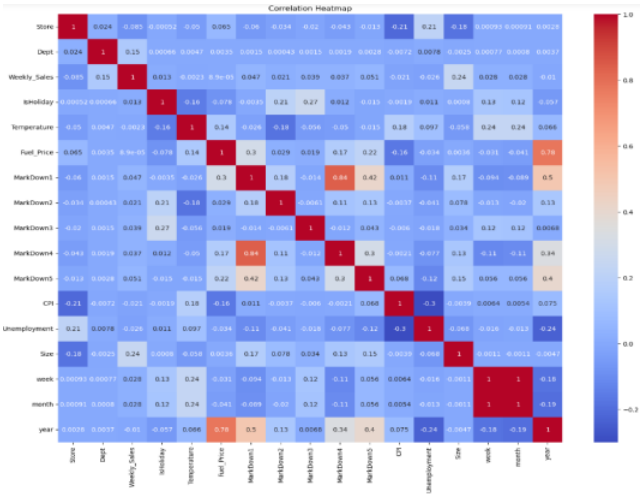

Figure 3: Correlation Analysis

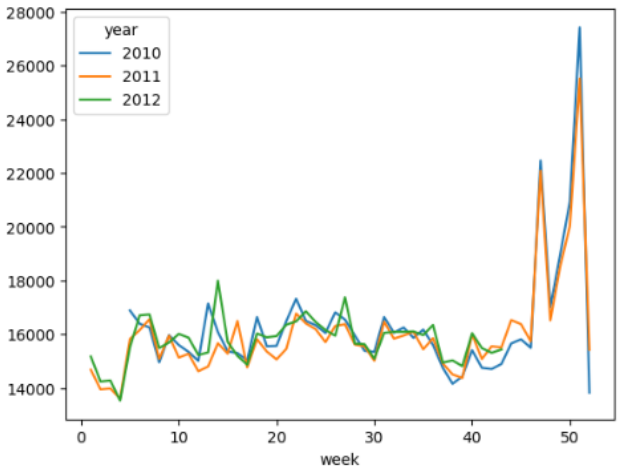

Figure 4: Top 5 sales averages by weekly belongs to 1-2 weeks before Christmas, Thanksgiving, Black Friday

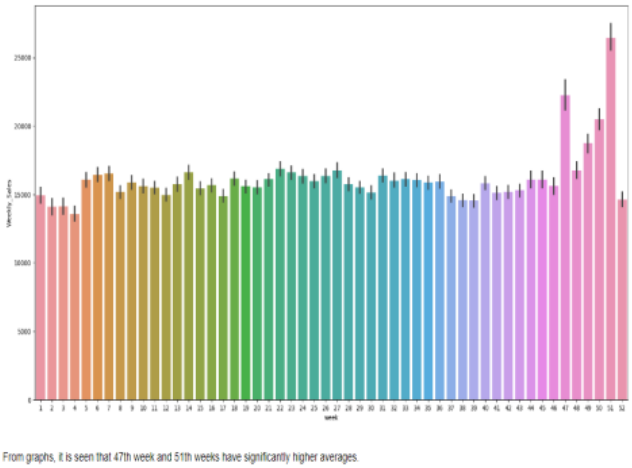

Figure 5: Weekly Sales Per Year

'TypeSize'.

To further enhance the dataset, I created rolling averages for 4 and 12 weeks, as well as lag features for the previous week. Finally, I applied label encoding again to make sure the features were in a suitable format for modeling.

5. Model Implementation: We have implemented a comprehensive range of models, including Linear Regression, Random Forest, LSTM, XGBoost, Holt-Winters, and ARIMA, which have been carefully selected for their ability to handle time series data and model complex relationships. With these powerful tools at our disposal, we are confident in our ability to deliver accurate and reliable results that meet your unique needs.

6. Model Evaluation: It is most important to evaluate the models thoroughly, considering various metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared. This allowed for a comprehensive comparison of each model's performance and helped in determining their accuracy while predicting sales.

7. Comparative Analysis: Then we conducted a comparative analysis, and we were able to determine the most optimal approach for sales forecasting within the Walmart dataset. The results of various models were evaluated to identify the most effective method, ensuring accurate and reliable predictions.

6. Results

The results from the evaluation of various forecasting models on the Walmart dataset present a comprehensive picture of their performance:

1. Linear Regression: Showed a high accuracy of 94.37

percent, indicating a strong fit to the data. The Mean Squared Error (MSE) was recorded at 30,038,883.34, and the R-squared value of 0.9437 reflects a high level of variance explanation by the model.

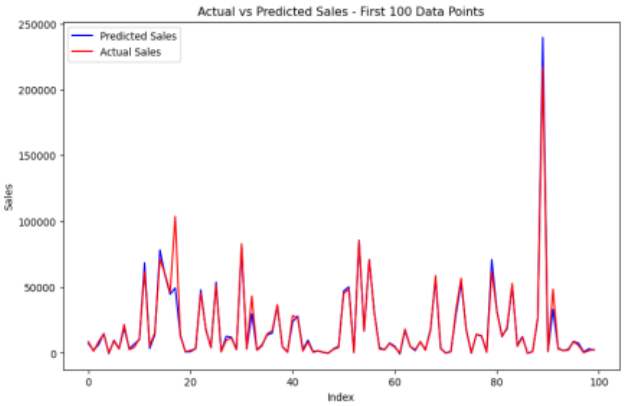

Figure 6: Linear Regression Actual Vs Predicted

2. Random Forest: Outperformed Linear Regression with an accuracy of 96.08 percent, demonstrating its effectiveness in capturing complex nonlinear relationships in the data. The MSE was considerably lower at 20,920,890.39, and an R-squared value of 0.9608 signifies an excellent predictive performance.

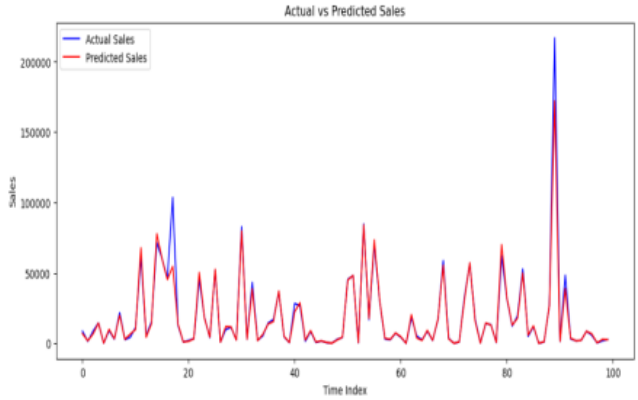

Figure 7: Random Forest Actual Vs Predicted

3. LSTM (Long Short-Term Memory): This model showed a significantly lower accuracy of 16.45 percent, with an MSE of 0.000603 and an R-squared Score of 0.1644, indicating limited effectiveness in this context, possibly due to overfitting or underfitting.

4. XGBoost: Excelled with the highest accuracy of 97.76 percent, and the lowest MSE at 11,962,011.93, accompanied by an impressive R-squared value of 0.9776. This indicates superior predictive ability and model fit.

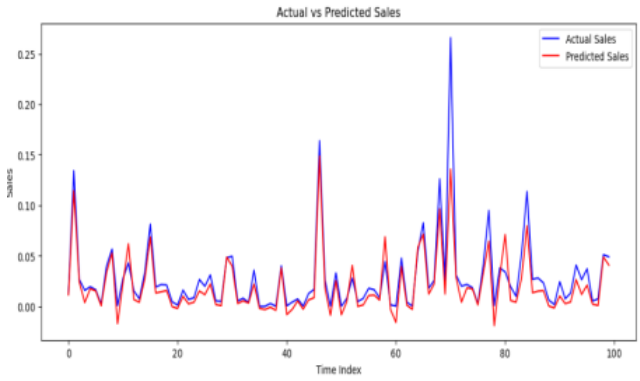

Figure 8: LSTM Actual Vs Predicted

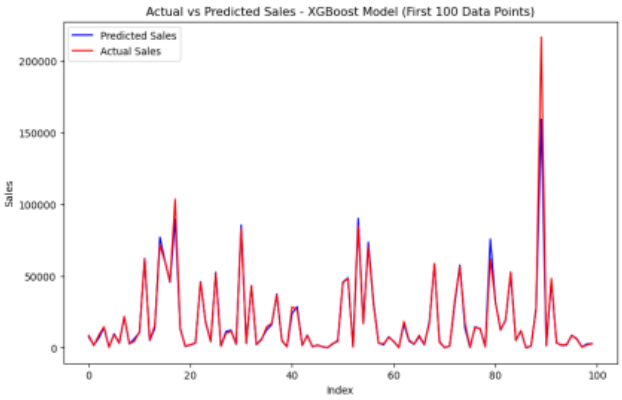

Figure 9: XGBoost Actual Vs Predicted

5. Holt-Winters: Demonstrated moderate accuracy at 63.57 percent, but with a significantly high MSE of 8,088,513,326.3, and an R-squared of 0.6356577, suggesting limited suitability for this particular dataset.

6. ARIMA (Exponential Smoothing Model): Had a negative R-squared value of -1.052142244335312 and an MSE of 1,616,960.316254969, indicating poor predictive performance in this context.

Comparative Analysis

Table 1 Shows the Comparative analysis of all the models:

Table 1: Comparative Analysis of Different Models

Model	Accuracy (%)	MSE	R-squared
Linear Regression	94.37	30038883.34	0.9437
Random Forest	96.08	20920890.39	0.9608
LSTM	16.45	0.000603	0.1644
XGBoost	97.76	11962011.93	0.9776
Holt-Winters	63.57	8088513326.3	0.6356577
ARIMA	N/A	1616960.316	-1.052142

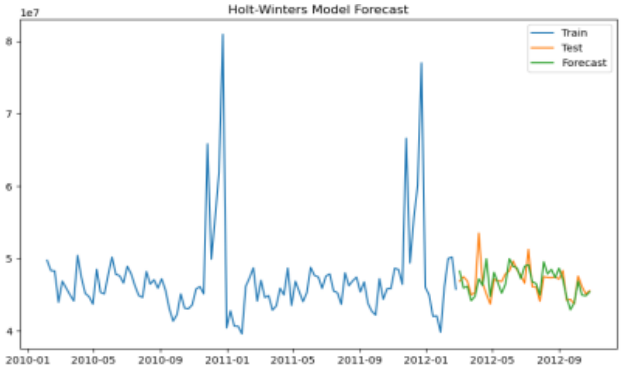

Figure 10: HoltWinters Actual Vs Predicted

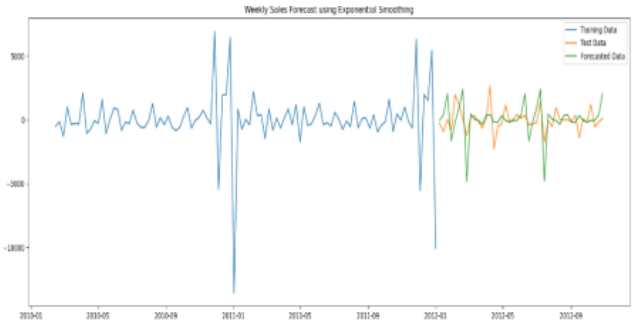

Figure 11: ARIMA Actual vs Predicted

7. Discussion

The results partially supports the hypothesis that advanced machine learning models are better than traditional statistical approaches for sales forecasting. Among advanced machine learning techniques, XGBoost and Random Forest demonstrated higher accuracy and lower mean squared error (MSE) than traditional models such as ARIMA and Holt-Winters. However, LSTM, another advanced model, performed significantly worse, possibly due to its sensitivity to the specific nature of the data, which requires fine-tuning. XGBoost and Random Forest exhibited strength in handling complex, nonlinear relationships in large datasets, while the limitations of LSTM and traditional methods such as Holt-Winters and ARIMA were exposed by their inability to accurately model the data. The differences in performance can be attributed to the inherent properties of these algorithms and their suitability to the characteristics of the sales data.

8. Future Work

The major shortcomings of the current method include the underperformance of the LSTM model and the limitations of traditional models like ARIMA and Holt-Winters in handling complex datasets. To overcome these, future work could focus on:

1. Enhancing LSTM Performance: Investigate and optimize hyperparameters, explore different network architectures, and implement advanced regularization techniques to improve LSTM's accuracy.

2. Hybrid Modeling: Combine strengths of different models, such as integrating machine learning models with traditional statistical methods to leverage their respective advantages.

3. Feature Engineering: Further refine the feature selection process to better capture influential factors affecting sales.

4. Data Augmentation: Incorporate additional data sources or synthetic data generation to enrich the training process and enhance model robustness.

These enhancements aim to address current limitations, potentially leading to more accurate and reliable sales forecasting models.

9. Conclusion

The project has successfully demonstrated the effectiveness of various machine learning and statistical models in sales forecasting. Among the models used, XGBoost and Random Forest showed exceptional performance in terms of accuracy and error metrics. The comparison of advanced models against traditional methods such as ARIMA and Holt-Winters highlights the superiority of machine learning techniques in handling complex, real-world datasets.

In conclusion, this project has the potential of advanced algorithms to significantly improve sales prediction accuracy. These findings cover the way for future research to focus on refining machine learning models, particularly in complex data scenarios. Moreover, this project provides a strong foundation for practical applications in business analytics. It highlights the importance of accurate sales forecasting for strategic decision-making and resource optimization.

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