

Fuel Sales Price Forecasting using Time Series, Machine Learning, and Deep Learning Models

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ABSTRACT

Advances in machine learning have led to an important shift in the petroleum service industry with the development of predictive analytics, using production records, staff data, and fuel sales profiles, to enhance machine learning-based systems that support decisions. These cutting-edge tools can forecast gasoline sales, identify significant trends, and pinpoint key factors that affect fuel sales. Fuel managers have a greater ability to make informed decisions, use resources efficiently, increase operational effectiveness, and increase sales of all fuel types based on the information obtained from these systems. Additionally, managers can efficiently manage risks while boosting efficiency by using predictive analytics and machine learning to quickly adapt to changes in the environment. This study proposes an innovative method for predictive fuel sales and pattern analysis, utilizing a real-life dataset from a service station in Jordan that features a real-time instant sales record, connected to an online sales system.

Keywords-smart sales prediction; machine learning; time-series; artificial neural networks; dataset

I. INTRODUCTION

Data-driven AI and machine learning models can enhance fuel sales management and decision-making. Machine learning techniques, from traditional methods to deep learning, can be used to analyze daily and long-term sales trends, demonstrating significant potential for optimizing fuel distribution strategies. Fuel sales are vital for economies, particularly in developing countries, supporting household incomes and energy security. In Jordan, Jopetrol, a major fuel distributor, collected comprehensive sales data from January 2023 to June 2024 using smart sensors and card readers to monitor various operational metrics [1]. A fuel service station located in Irbid City, north Jordan, uses sensors and card readers on each fuel pump to track daily sales and operational metrics, such as fuel levels, pump activity, maintenance requirements, and up to 13 different attributes.

The integration of AI in the fuel industry has revolutionized sales practices, improving efficiency in inventory management, sales forecasting, quality control, supply chain optimization, and customer service. Advanced AI tools allow fuel distributors to make data-driven decisions, reduce costs, and improve operational performance through automated monitoring systems. AI-powered analytics provide actionable insights, allowing companies to anticipate market trends and adjust their strategies accordingly [2].

This study evaluates machine learning algorithms for fuel sales forecasting at two levels: short-term (daily sales) and long-term (monthly sales). It aims to classify sales into categories (low to very high) and provide quantitative sales estimates using classification and regression models. In [3], the

focus was on traditional yet comprehensive sales forecasting to aid budgeting and financial planning. SG Trading, a Filipino-owned company in Quezon City, was examined, combining existing studies with quantitative analysis to improve forecast accuracy. In [4], statistical models (ARIMA, ARMA) and machine learning models (SVM, RF, and XGBoost) were compared in forecasting SG Trading's LPG sales. XGBoost proved to be the most accurate with minimal error, making it ideal for supply planning. Future improvements were proposed, such as adding more variables to improve forecast accuracy and business sustainability.

Retail is a key area in data science dealing with vast amounts of data and optimization challenges, such as pricing, recommendations, and inventory management. Sales predictions are crucial in today's dynamic market, helping businesses reduce costs and improve efficiency. Even small improvements enhance sales, optimize operations, and boost customer satisfaction [5]. In [6], a comprehensive forecasting approach was applied to help companies plan budgets and future expenses. Experiments were used to analyze traditional statistical models such as ARIMA and ARMA and assess their effectiveness in quantitative sales forecasting. Business intelligence involves collecting and analyzing data to support informed decision-making. In [7], existing forecasting techniques along with the impact of customer data on predictions were examined. This study aimed to develop a hybrid approach, integrating customer-centric analysis with traditional sales forecasting. In [8], the aim was to build a cognitive analytic framework using machine learning to improve the accuracy of the retail sales forecast. By combining statistical, machine learning, and deep learning models, it achieved an accuracy of up to 90%. This method was

particularly effective in e-commerce for estimating product-level demand and capturing variable trends.

Success in customer-focused businesses requires strong communication between management and marketing. In [9], a data mining method was proposed to create a customer profile system, incorporating action prediction and equity assessment. Using RFM analysis and boosting trees, this study emphasized the importance of algorithms and segmentation to enhance sales forecast accuracy. Machine learning is transforming industries such as marketing, sales, healthcare, and education by enabling better customer insights and sales predictions. In [10], machine learning models, such as Linear Regression (LR), RF, and XGBoost, were used to forecast sales for big-box retailers based on historical data and key product attributes. This study also focused on real-time fuel price prediction using an Elman neural network to predict diesel price fluctuations and daily sales. In [11], data mining techniques were explored for retail sales forecasting, comparing algorithms such as multiple LR, RF, and SVM to predict sales at 45 Walmart outlets. This approach considered factors such as past sales, holidays, promotions, and economic indicators. The goal was to help companies select the best model for forecasting and optimizing marketing strategies.

This study developed data-driven machine-learning models to improve fuel sales management and decision-making. Machine learning techniques, from traditional methods to deep learning, can be used to analyze daily and long-term sales trends, demonstrating significant potential for optimizing fuel distribution strategies. The findings of this study align with previous studies that highlight the effectiveness of machine learning models over traditional time series methods in fuel sales forecasting. Although ARIMA and SARIMA capture long-term trends, they struggle with sudden fluctuations. Deep learning models, such as LSTM, have shown strong performance in sequential data. However, the results of this study show that Random Forest (RF) outperformed LSTM in handling volatile fuel sales data. This differs from previous studies that emphasized the strength of LSTM, suggesting that tree-based models may be better suited for highly dynamic sales environments. To improve generalization, future research should explore ensemble methods, combining RF with deep learning to optimize accuracy under different market conditions.

II. DATASET DESCRIPTION

Patterns in fuel usage offer significant data on consumer behavior, environmental effects, and market dynamics. Service stations are key points of data collection for fuel sales, delivering rich datasets that can be utilized for machine learning and analytics predictions. This study examines a dataset that includes 258,900 fuel sales across various fuel types between January 2023 and June 2024 with 13 variables. The main objectives were to understand the sales patterns, consumer preferences, and variables that affect the cost of gasoline. The first step in the proposed method is data preprocessing.

TABLE I. FUEL SALES DATASET DESCRIPTION

Feature	Description
Date	Day. Month. Year
Datetime	Day. Month. Year 00:00:00
Sales Type	Cash or VIS (VIS for government vehicles with electronic tags)
Payment	Cash or Credit
Tank	Tank number
Pump	Pump number
Nozzle	Nozzle number
Group	Group number of attendant, blank attribute with no entry
Attendant	Staff name of attendant at pump
Product	Gasoline (Unleaded 90), Diesel or Kerosine
Unit Price	Unit price per liter
Sales Amount	Sales amount in liter
Sales Price	Total amount paid in JD

A. Preprocessing and Experimental Setup

Irrelevant columns, such as Payment Type and Group, were dropped. Dates were converted to proper datetime formats for the Date and Datetime Attributes. The attendant column had 2124 missing values. Since the missing values were only in the attendant column and did not affect analysis tasks, the missing values for Attendant were filled with "Unknown". Table II shows a sample of the dataset.

TABLE II. PREPROCESSING RESULTS

#	Date	Hours	Sales	Type	Tank	Pump	Noz.
0	2023-01-01	07:23:30		Cash	2	4	1
1	2023-01-01	07:23:38		Cash	2	3	1
2	2023-01-01	07:24:34		Cash	2	3	1
3	2023-01-01	07:28:41		Cash	1	5	1
4	2023-01-01	07:32:14		Cash	2	4	1

III. DATA VISUALIZATION

The following plots were created. Histograms were created for numerical columns such as Unit Price, Sales Amount, and Sales Price. Unit Price appears to have a limited range of values, which makes sense given that it is tied to the product being sold, e.g. Gasoline or Diesel. Sales Amount has a more spread-out distribution, showing a mix of small and large sales. Sales Price also shows variability, reflecting different quantities being sold at different prices.

The scatter plot in Figure 2 visualizes relationships between variables. There is a clear positive relationship between Sales Amount and Sales Price, as expected since higher amounts sold lead to higher prices.

As shown in Figure 3, box plots reveal outliers in Sales Amount and Sales Price distributions, while Unit Price shows more consistent values within expected ranges. These outlier transactions represent unusually large sales volumes that require further analysis.

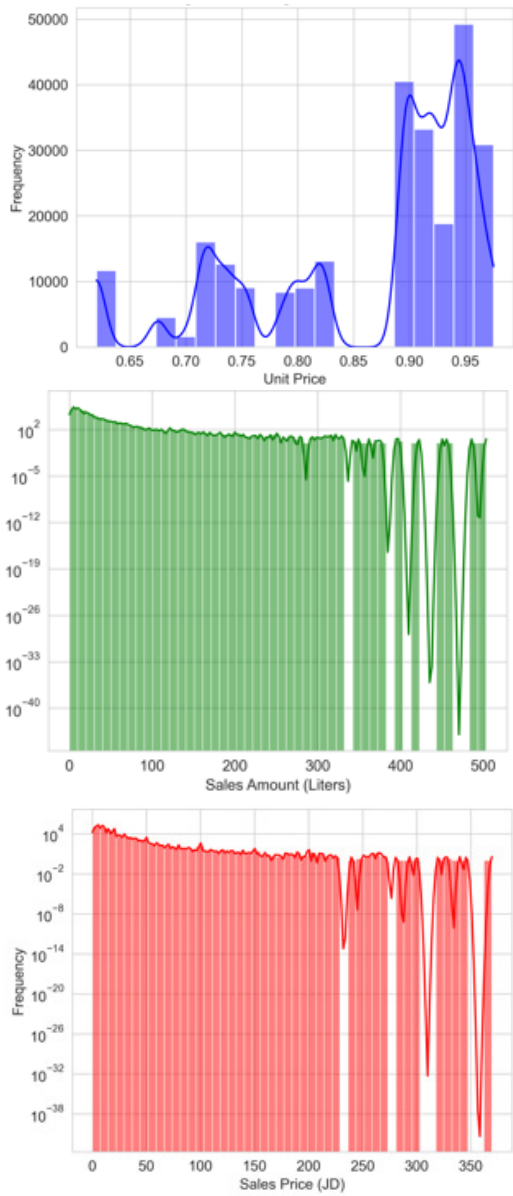


Fig. 1. Histogram results.

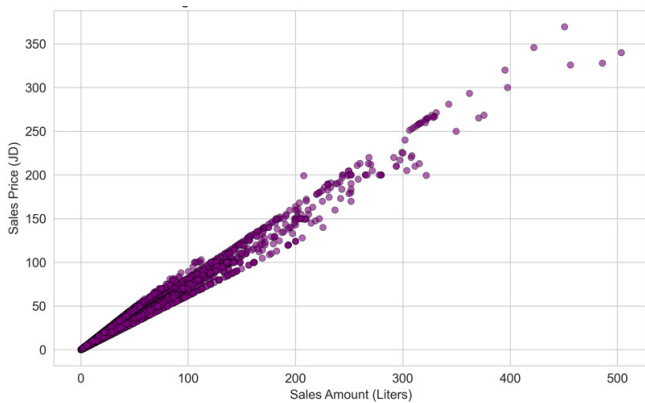


Fig. 2. Sales amount vs Sales price.

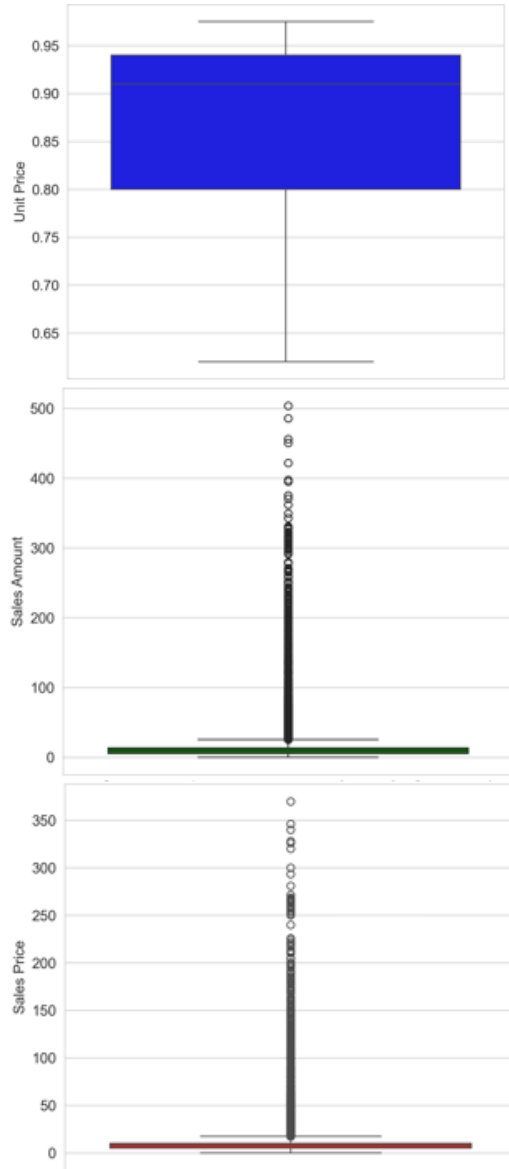


Fig. 3. Distribution box plots to detect outliers in Unit Price, Sales Amount, and Sales Price.

IV. SUMMARY STATISTICS

The summary statistics involved calculating the Mean, Median, mode, Standard Deviation, etc., for the numerical columns (Unit Price, Sales Amount, Sales Price). The dataset shows a mixture of typical sales and some extreme values, as indicated by the range of values for Sales Amount and Sales Price.

V. CORRELATION ANALYSIS

In this step, the correlation between the numerical variables Unit Price, Sales Amount, and Sales Price was examined to understand the relationships between them. Examining Unit Price with Sales Amount showed a weak negative correlation (-0.19), suggesting that as the unit price decreases slightly, the sales amount tends to increase, although this relationship is not

strong. Examining Sales Amount with Sales Price showed a strong positive correlation (0.99), indicating that higher sales amounts almost always lead to higher sales prices. Examining Unit Price with Sales Price showed a weakly negative correlation (-0.08), suggesting a small relationship. Table II presents a summary of statistics for the data used in this study.

TABLE III. SUMMARY OF STATISTICS

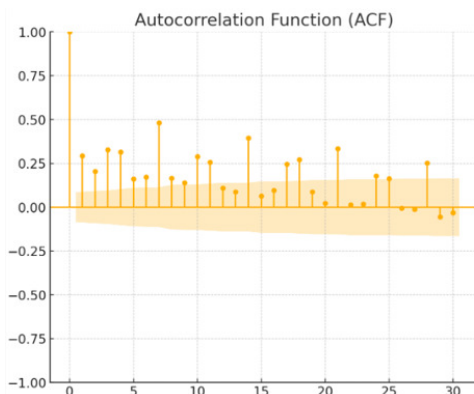
Result	Unit Price	Sales Amount	Sales Price
Count	258890	258890	258890
Mean	0.866482	11.588591	9.808223
St. Dev.	0.098543	12.416628	9.700083
Min	0.620000	0.000000	0.000000
25%	0.800000	5.376000	5.000000
50%	0.910000	9.589000	8.000000
75%	0.940000	13.333000	10.000000
Max	0.975000	503.54300	369.55400

VI. MODEL SELECTION AND EVALUATION

To select and evaluate models, a time series analysis was first conducted using ARIMA and SARIMA [12]. Then, machine learning models, such as linear regression, DT, and RF, and deep learning models (LSTM, GRU) were used for forecasting. Since sales data varies over time, the Datetime column serves as the time index. Forecasting sales prices with ARIMA and SARIMA helps identify trends and seasonal patterns. Machine learning models refined predictions by capturing complex relationships in the data. Combining statistical and deep learning approaches enhances forecasting accuracy for better decision-making. This hybrid strategy allows businesses to optimize pricing, manage inventory, and improve financial planning.

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots help to determine the parameters for ARIMA. Based on these plots, the ARIMA model be used with the following steps:

- *p* (AR term): PACF suggests that the autoregressive term (*p*) might be 1 or 2.
- *d* (differencing): Since the data show some trend, one level of differencing (*d* = 1) may be needed.



- *q* (MA term): The ACF suggests that the moving average term (*q*) could be 1.

Based on the above parameters, the ARIMA model was used to fit the data and evaluate the results.

TABLE IV. ARIMA FORECAST RESULTS FOR THE NEXT 30 DAYS

Dep. variable:	Sales Price	No. of observations:	529	Log Likelihood	-4263.847
Model:	ARIMA (1, 1, 1)	AIC	8533.695	BIC	8546.502
Date:	Thu, 17 Oct 2024	HQIC	8538.709	Sample:	01-01-2023 - 06-12-2024
Covariance type:	opg				
	coef	std err	z	P> z	[0.025 & 0.975]
ar.L1	0.018	0.046	0.391	0.696	(-0.072 0.109)
ma.L1	-0.8743	0.028	-30.984	0	(-0.930-0.819)
sigma2	658600	26700	24.702	0	(6.06e+05 7.11e+05)
Ljung-Box (L1) (Q):	0.01	Jarque-Bera (JB):	334.7	Prob(Q):	0
Heteroskedacity (H):	0.83	Skew:	-0.77	Kurtosis:	6.58

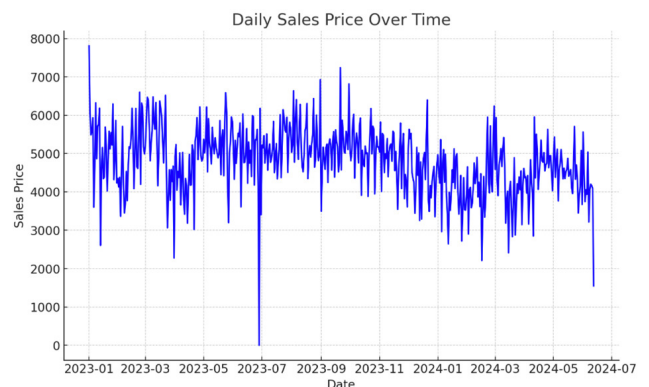


Fig. 4. ARIMA analysis, daily Sales Price over time.

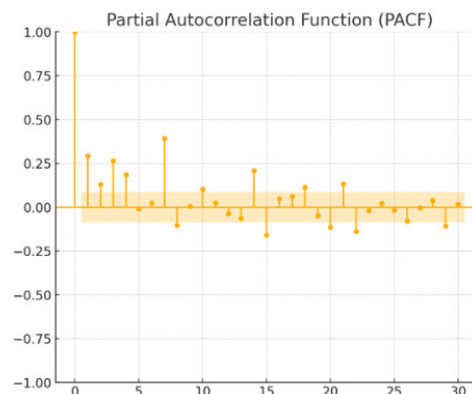


Fig. 5. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).

To address seasonal patterns in the fuel sales data, the ARIMA model was extended with seasonal components using SARIMA (Seasonal ARIMA) [13], which can capture weekly and monthly patterns in addition to the overall trends in price changes. The SARIMA model (1,1,1)×(1,1,1,7) was used to incorporate weekly seasonality (7-day periods). Both Auto-

Regressive (AR) and Moving Average (MA) components showed statistical significance, with the seasonal MA term having particularly strong predictive factors. The forecast for the next 30 days shows a trend that accounts for seasonality, as shown in Figure 7. The improved AIC score of 8237.199 shows a better model compared to the base ARIMA.

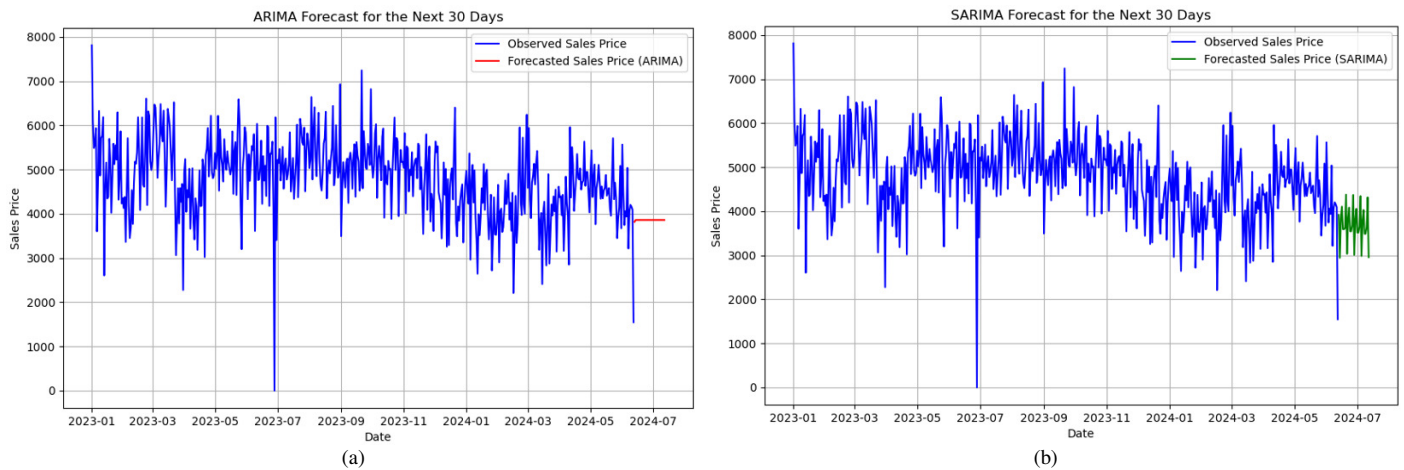


Fig. 6. ARIMA (a) and SARIMA (b) forecasts for 30 days.

VII. MACHINE LEARNING MODELS FOR FORECASTING

Machine learning models, namely LR, DT, and RF [14], were implemented using the same features to predict the target variable. Data were split into training and test sets followed by fitting and evaluating each model. The linear regression model used the following features: Unit Price, Sales Amount, Tank, Pump, and Nozzle. As shown in Table V, the LR model had a Mean Squared Error (MSE) of 1.41, which is the average squared difference between the predicted and actual Sales Price. The R-squared (R^2) of 0.986 indicates that the model explains approximately 98.6% of the variance in Sales Price, suggesting a good fit. The DT model's MSE of 0.082 was significantly lower than that of LR, indicating very accurate predictions. The R^2 of 0.999 shows that the model explains nearly 100% of the variance in Sales Price, suggesting an excellent fit. The RF model had an MSE of 0.071, which was slightly better than the DT model, indicating very accurate predictions, and the R^2 of 0.999 was similar to the DT, showing that it explained almost 100% of the variation in Sales Price.

TABLE V. LR, DT, AND RF MODELS' RESULTS

	MSE	R^2
LR	1.409	0.985588
DT	0.082	0.999158
RF	0.071	0.999273

Summarizing the results of the machine learning models used, both the DT and RF models performed exceptionally well, with RF slightly outperforming in terms of accuracy. The performance of the RF model indicates that it can capture complex sales patterns.

As there was a concern that R^2 values of 0.999 indicated overfitting, these models were further tuned achieving the results in Table VI. The models no longer overfit, as the training and test R^2 scores are close (~0.98-0.99), indicating good generalization. Cross-Validation (CV Mean R^2) confirms strong generalization (0.978-0.982). Test MSE is close to training MSE, meaning that the models perform consistently on new data. Key changes that resolved overfitting were limiting tree depth (`max_depth = 5`) restricting splits (`min_samples_split = 5`, `min_samples_leaf = 2`), and cross-validation (`cv = 5`) to validate generalization.

TABLE VI. DT, AND RF DETAILED RESULTS

	Training R2	Test R2	Training MSE	Test MSE	CV mean R2
D	0.984202928	0.982177651	1.471763901	1.742750658	0.978826845
T	4694032		7388318	3353036	4709691
R	0.986457566	0.985299805	1.261706313	1.437452090	0.982332247
F		9120742	763931	2032668	3253493

VIII. DEEP LEARNING MODELS FOR TIME SERIES FORECASTING

Two deep learning models, LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Units), were also examined for the same purpose. These models are designed to handle sequential data and are often used for time-series forecasting. Figure 7 shows that actual prices had high variability and volatility, with frequent peaks and drops in Sales Price. The GRU predictions are much smoother and less volatile, showing that the GRU model struggles to fully capture the fluctuations in the actual data. Although it manages to predict the general trend, it underestimates the spikes and overestimates the dips. Figure 8 shows that the LSTM

predictions were better than GRU's in capturing data variations. The LSTM model aligns more closely with the actual values and tracks trends and volatility to a greater extent. However, it still shows some smoothing and does not fully capture the extreme spikes in sales prices. As a general observation, LSTM performs better than GRU for this dataset, capturing more of the volatility and short-term fluctuations.

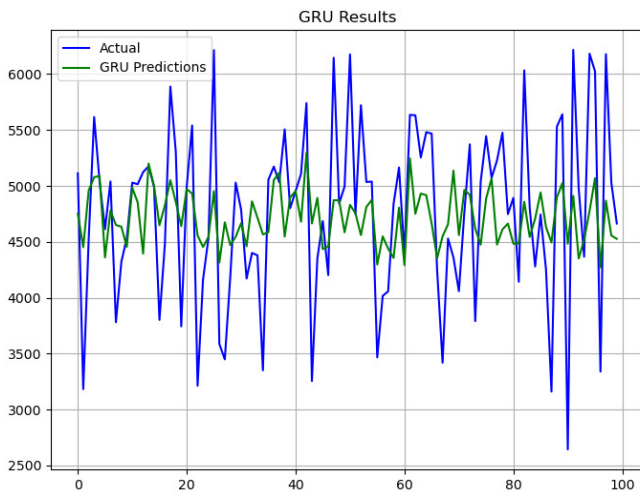


Fig. 7. GRU results.

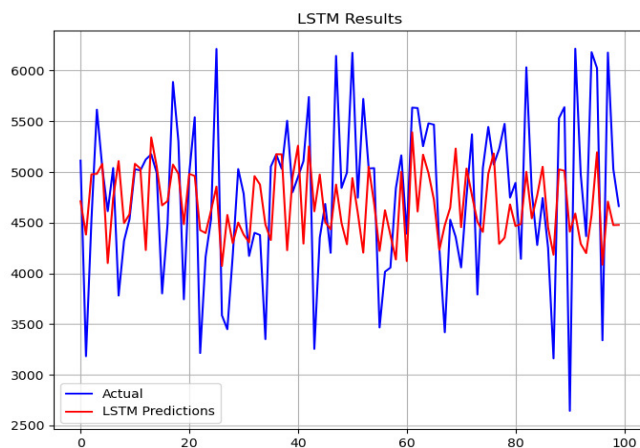


Fig. 8. LSTM results.

However, both models struggle with extreme spikes and dips, suggesting that further tuning or additional features may be needed to improve forecast accuracy. Ensemble methods could also be considered for more advanced models to further capture the complexity of the data. A comparative analysis of sales price forecasting models reveals that time series models such as ARIMA and SARIMA perform best on datasets that exhibit strong seasonality and unambiguous patterns, but they suffer from high levels of volatility. The best-performing machine learning models managed volatility, captured linear and nonlinear patterns, and produced great accuracy, with RF standing out. DT performed well but ran the danger of overfitting, and LR missed the complexity required for this problem. Although both GRU and LSTM are deep learning

models, LSTM performed better than GRU in handling short-term variations and trends. But when it came to controlling excessive volatility, both behaved less accurately than RF [15].

IX. DISCUSSION OF FINDINGS

This study identified RF as the most accurate model for fuel sales forecasting, outperforming traditional time series models such as ARIMA and SARIMA. This aligns with previous research that showed that machine learning models, particularly tree-based algorithms, handle complex and volatile datasets more effectively than classic statistical approaches. Similar studies in fuel sales forecasting have found ARIMA and SARIMA useful for capturing long-term trends but less effective in managing sudden fluctuations, reinforcing the conclusion of this study.

However, some previous studies suggest that deep learning models, particularly LSTM, perform well in sequential data forecasting because of their ability to capture temporal dependencies. Although LSTM was the second-best model in this study, its slight underperformance compared to RF may be due to the high volatility and relatively short historical trends of the dataset, which tree-based models handle more effectively. Other studies have demonstrated improved results by combining LSTM with additional external factors, such as economic indicators and weather conditions, which were not fully integrated into this research. Overall, the results align with existing research advocating machine learning over traditional statistical methods. However, discrepancies in model results suggest that incorporating hybrid approaches or additional features could further enhance forecast accuracy. Future studies could explore ensemble techniques that blend RF with deep learning models to optimize fuel sales predictions in volatile markets. Using data from one fuel station limits generalization, as it may not reflect regional demand, pricing, or consumer behavior. This increases the risk of overfitting, making the model less effective elsewhere. Future research should use multi-location data for better accuracy.

X. CONCLUSION AND RECOMMENDATIONS

The RF model emerged as the most effective, achieving the highest accuracy ($R^2 = 0.999$) and the lowest MSE, making it ideal for managing both data complexity and volatility. Its ability to capture intricate relationships and adapt to sudden changes in sales trends makes it the preferred choice for this dataset. LSTM followed as the second-best model, excelling in handling time-series data and volatility, being better than GRU and traditional models such as ARIMA and SARIMA. However, despite its strengths, LSTM still falls slightly behind RF in overall performance.

Time-series models such as ARIMA and SARIMA are useful for identifying long-term patterns but struggle to adapt to sudden fluctuations, limiting their effectiveness in highly volatile datasets. Given these findings, RF is recommended for forecasting in dynamic environments, where rapid changes in data patterns are common. Meanwhile, LSTM remains a strong alternative for sequential data with less volatility or more complex dependencies. Future research could explore hybrid approaches, combining the strengths of tree-based models and

deep learning to further enhance forecast accuracy and adaptability. In addition, integrating external factors such as economic indicators, market trends, and seasonality could refine prediction models for better performance. Combining feature engineering with advanced models may improve accuracy by reducing the noise in the data. Hyperparameter tuning and model optimization should be further explored to maximize predictive potential. Leveraging ensemble learning techniques, such as combining RF with deep learning models, may lead to more robust forecasting strategies. Ultimately, companies can achieve better decision-making by adopting adaptive AI-driven models tailored to their unique data challenges.

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