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Multi-Channel Sales Forecasting in a Kenyan Retail Environment

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***Abstract*— The fast and continuous progress in technology is significantly impacting not only the dynamics of retail and e-commerce but also the innovations in sales forecasting. Identifying what could potentially be the most effective method available for predicting sales across online and offline sales channels in this rapidly growing market is becoming more and more crucial to business owners. This study on multi-channel retailing examines the performances of conventional time series forecasting models ARIMA/SARIMA and the more recent approaches like Facebook Prophet and RNN. For this purpose, Kenyan retail time series data of three years was utilized. Our findings highlight that among these methods, LSTM emerges as the top performer, demonstrating superior accuracy in capturing the complex characteristics of the sales data. It is also important to note that based on the results of the experiments, SARIMA still has potential especially in short-term predictions of time series with strong seasonality.**

***Keywords*— ARIMA, Facebook Prophet, RNN, LSTM**

I. Introduction

The multi-channel retail sector in Kenya, like that of other developing countries, has seen rapid growth in recent years, and as the second most formalized in Africa according to Oxford Business Group [1], it indicates a strong foundation for business growth, especially within the booming e-commerce space. In a multi-channel Retail business multiple channels are used to sell similar products on various platforms. Common types of multi-channel retailing are Online store, Physical store, Online marketplaces and catalog. Kenya being the economic, commercial, financial, and logistics hub of East Africa [2], it presents a valuable opportunity for analysing sales patterns. With its expanding traditional retail and thriving e-commerce, accurate sales forecasting becomes essential, and understanding the complex interplay between these channels enables businesses to make informed decisions in inventory management, marketing strategies, and overall business planning.

Sales forecasting is a tool that allows companies to anticipate shifts in consumer behavior, optimize resource allocation, and ultimately stay ahead in the competitive and rapidly evolving market [3]. Some popular time series forecasting models used for this purpose include Moving Average (MA), Exponential Smoothing, and ARIMA/SARIMA.

The ongoing advancements in machine learning and computing power are leading to the development of even more sophisticated forecasting models. This is becoming much more significant for retail sales data where intricate, non-linear relationships are commonplace. Traditional techniques demonstrate good results [4], but newer models such as RNNs and Facebook Prophet offer more promising capabilities in capturing complex patterns, potentially leading to enhanced forecasting accuracy.

This study explores the performance of both traditional and modern forecasting models in a Kenyan retail environment. We will be using the forecasting models Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) alongside the newer methods, RNN and Facebook Prophet. The results will hopefully reveal whether the more recent models are superior to their predecessors.

II. Literature Review

Numerous studies in the past have explored the comparative analysis of time series forecasting models aiming to determine the most effective approach for different use cases. These researches examined the strengths and weaknesses of the various methods. Some of them focused on the performance of specific domains while others focused on the different characteristics of the data such as seasonality, trend, etc.

Weytjens et al [5] conducted a study on cash flow prediction comparing the performance of different forecasting methods such as Multilayer Perceptron, Long Short-Term Memory (LSTM) Neural Networks, the classic ARIMA, and Facebook's Prophet. Their findings revealed a significant advantage for LSTM, clearly outperforming the other techniques in accurately forecasting cash flows. Instead of relying solely on standard performance metrics like Mean Squared Error (MSE) and Mean Absolute Error (MAE), they introduced their metric called Interest Opportunity Cost (IOC) which quantifies how much money is lost using the discrepancies between the predicted and actual cash flows. By incorporating this metric, they were able to provide a more comprehensive evaluation of the models' effectiveness in a real-world financial context.

Zeng et al [6] challenged the sophisticated Transformer-based LSTF model with a simple one-layer linear model called LSTF-linear on nine real-life datasets.

In a 2014 study, Adebiyi et al [7] detailed the extensive process of stock price prediction using the ARIMA model. They used two stock price datasets, one from NYSE and the other from NSE. The results demonstrated that ARIMA can be a good option for short-term predictions.

III. Methodology

In this research, R programming language and libraries are used to perform exploratory data analysis, data preprocessing, model training, and model evaluation.

A. Data Gathering

The dataset used in this study was sourced from Kaggle, an online platform providing various data science resources and an online community for data scientists and machine learning practitioners [18]. The data consists of three-year historical sales transactions of a Kenyan retail business focusing on selling baby products [19].

B. Exploratory Data Analysis

Fig. 1 is the time series plot of the total weekly sales for Online and Offline Sales Channels. It can be observed that there is a slight uptrend in both series.

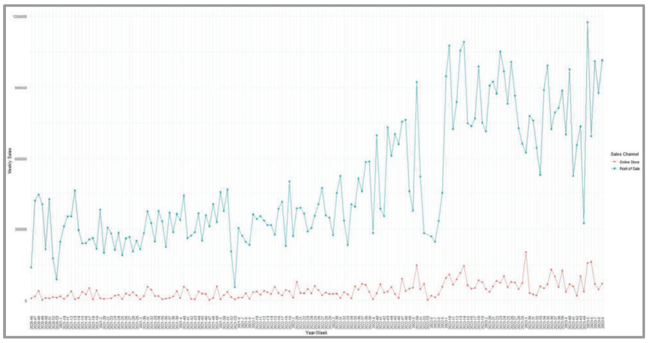

Fig. 1 Weekly Sales - Online vs. Offline Sales

The slight uptrend is more noticeable in Fig. 2 where the monthly data is presented, show comparison of offline and online sales from November 2020 to October 2023. Fig. 3 shows the distribution of sales on different holidays in Kenya. There is hardly any noticeable significant spike or drop in the sales data relating to the holidays. An additive decomposition is performed on the time series to gain more insights into the data. The insight provides a clearer view of how the different factors such as trend, seasonality, and noise influence the data and help in the model selection and implementation stages.

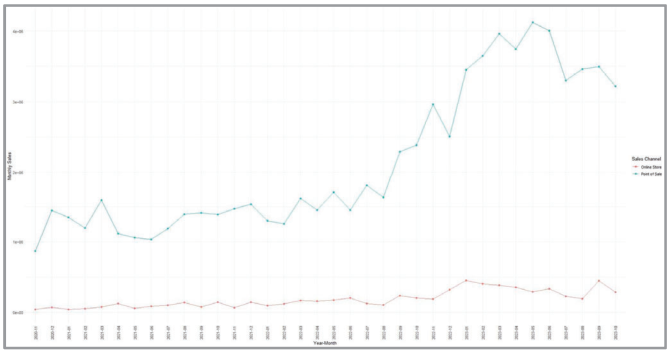

Fig. 2 Monthly Sales - Online vs. Offline Sales

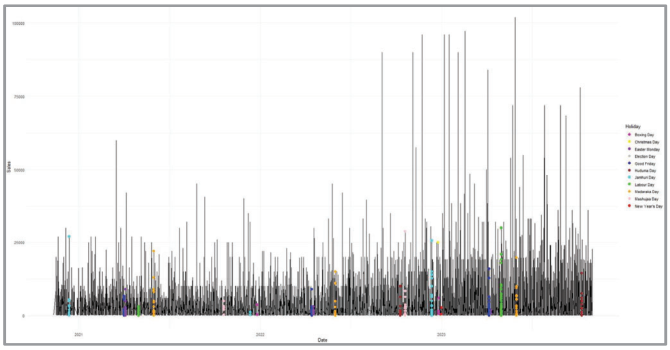

Fig. 3 Distribution of Sales Across Holidays

Fig. 4 is the decomposed time series of the Online Kenyan Sales data of baby products. It demonstrates strong seasonality and a slight uptrend. Offline Sales data demonstrates a strong seasonality similar to the previous one and a slightly more noticeable uptrend as seen in Fig. 5.

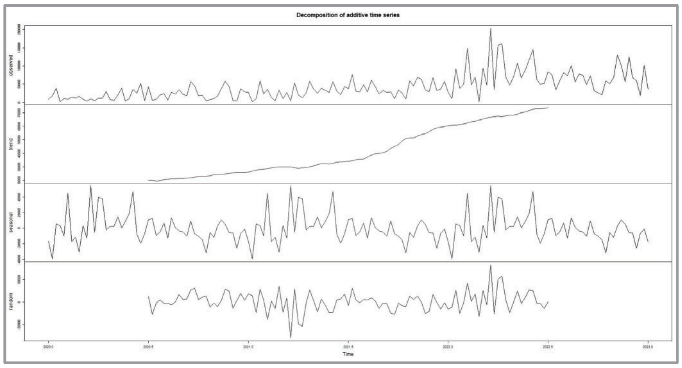

Fig. 4 Time Series Decomposition (Online Sales)

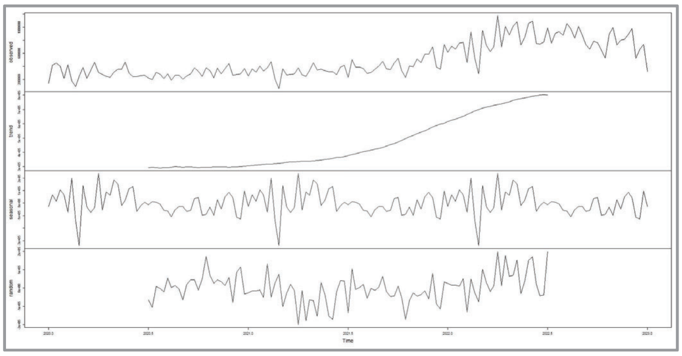

Fig. 5 Time Series Decomposition (offline Sales)

C. Data Preprocessing

The time series data of sales include actual sales, returns, also draft orders. For experiment focus is mainly on actual sales that generated revenue so data needed preprocessing. Several pre-processing steps were performed on the dataset to achieve the most accurate results possible.

- *Returns* have been filtered out from the dataset because they do not contribute to the actual sales figures and can mislead the analysis.
- *Draft Orders* were also removed because they are not considered finalized sales and could skew the analysis of completed sales transactions.
- *Kenyan Holidays* were attached to the sales records so that their possible effects on the data can be analyzed.

The holidays are New Year's Day, Good Friday, Easter Monday, Labour Day, Madaraka Day, Huduma Day, Mashujaa Day, Jamhuri Day, Christmas Day, Boxing Day and Election Day (2022-08-09).

D. Model Selection and Implementation

First, we chose traditional forecasting models ARIMA and SARIMA. We then tried to incorporate holidays and used Facebook Prophet, Simple RNN and LSTM [20-21].

1. ARIMA

Autoregressive Integrated Moving Average Model (ARIMA) is a statistical approach that models a time series as a function of its past values (Autoregressive Component), past forecasting errors (Moving Average Component), and the degree of differencing needed to achieve stationarity (Integrated Component) [8]. A stepwise approach was followed to identify the most suited ARIMA model (p, d, q) based on different statistical tests.Augmented Dickey-Fuller (ADF) Test was used to check if the time series is stationary. Table I shows the result of the ADF Test of the Online Sales time series. Having an ADF Test Statistic score of -4.3263 suggests strong evidence against the null hypothesis that the series has a unit root. Also, a p-value of 0.01 which is way less than the common significance level of 0.05 suggests that the time series is stationary.

Table II shows the result of the ADF Test of Offline Sales time series. With a p-value of 0.4072 which is significantly higher than 0.05, the result suggests that the series is non-stationary.

TABLE I. AUGMENTED DICKEY-FULLER TEST RESULTS (ONLINE SALES)

Dickey-Fuller	-4.3263
Lag order	5
p-value	0.01

TABLE II. AUGMENTED DICKEY-FULLER TEST RESULTS (OFFLINE SALES)

Dickey-Fuller	-2.4058
Lag order	5
p-value	0.4072

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were examined to determine the most appropriate (AR) and (MA) order. Fig. 6 is the plot of the ACF for the Online Sales. It exhibits moderate positive autocorrelation at lower lags which means past values have some influence on future values.

These moderate autocorrelations at lower lags suggest that it could be beneficial for short-term forecasting. The decrease in correlation over time, however, indicates that long-term forecasting may be challenging and less reliable. [8, 9, 11, 12, 13, 14, 15]

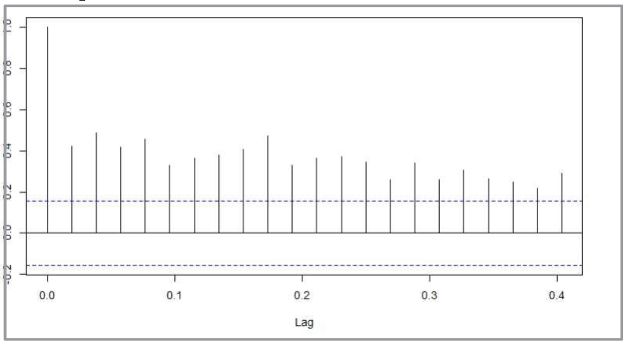

Fig. 6 Autocorrelation Function Plot (Online Sales)

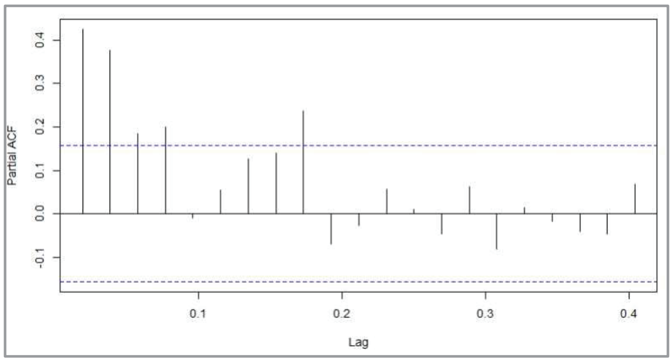

Fig. 7 Partial Autocorrelation Function Plot (Online Sales)

Fig. 7 is the plot of the PACF for the Online Sales. There is a noticeable sharp drop after the first two lags suggesting that an AR (2) model might be appropriate for this series. Fig. 8 is the plot of the ACF for the Offline Sales. It exhibits consistently high autocorrelation values suggesting that past sales values are highly predictive of future sales values. Fig. 9 is the PACF plot of the Offline Sales. It shows spikes at lags 1 and 3 suggesting that an AR (1) or AR (3) model might be appropriate for this particular series.

The best ARIMA model for the Online Sales time series was ARIMA (0,1,1). The series is stationary based on the ADF Test but an order for differencing and MA helped improve its performance resulting to a BIC of 2893.18 and an AICc of 2884.92.For the Offline Sales time series, the best ARIMA model was ARIMA (1,1,2). It followed the ACF/PACF test's suggestion to incorporate an AR (1) or AR (3). It returned a BIC of 3273.59 and an AIC of 3262.65.

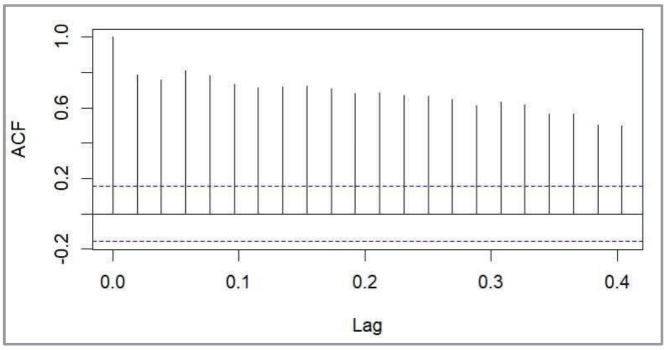

Fig. 8 Autocorrelation Function Plot (Offline Sales)

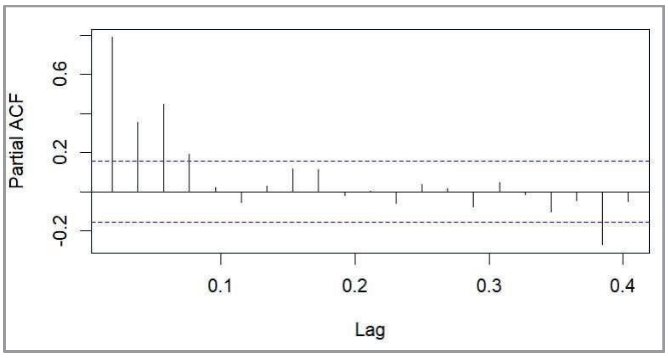

Fig. 9 Partial Autocorrelation Function Plot (Offline Sales)

2. SARIMA

Seasonal Autoregressive Integrated Moving Average Model (ARIMA) is an extension of ARIMA that explicitly captures recurring seasonal patterns within a time series. Its structure is represented as (p,d,q)(P,D,Q)_s, where the additional parameters (P,D,Q) represent seasonal components and 's' denotes the seasonal period [8]

We've observed seasonality on both the Online and Offline Sales time series; thus, we believe that SARIMA would be a good fit.

After various tests, the best models were ARIMA (1,1,1) (0,1,0) [52] for the Online Sales time series and ARIMA (2,1,0) (0,1,0) [52] for the Offline Sales time series. The BIC and AICc results were (BIC = 2893.18, AICc = 2884.92) and (BIC = 1916.74, AICc = 1910.26) respectively.

3. Facebook Prophet

Prophet is an open-source forecasting procedure developed by Facebook that decomposes a time series into trend, seasonality, holidays, and potential effects from exogenous variables [5]. It is known for its ease of use and handling of outliers [7]. We incorporated Kenyan holidays into the Prophet model to account for potential sales fluctuations associated with these days/weeks.

4. RNN

Recurrent Neural Network is a type of artificial neural network designed to process sequential data by maintaining a hidden state that captures information about previous inputs. RNNs are characterized by their ability to handle input sequences of variable length and to model temporal dependencies in data. [16]

One of the most common RNN architectures used in time series forecasting is the Long Short-Term Memory (LSTM) network which was introduced by Hochreiter and Schmidhuber in 1997 [17]. LSTMs address the vanishing gradient problem faced by traditional RNNs, enabling them to learn long-term dependencies more effectively.

In this study, we used *R's* '*reticulate'* package to set up a virtual environment and be able to integrate Python and Tensorflow into the workflow.

We tried both Simple RNN and LSTM to see which one would give us more favourable results. The architecture consisted of two Simple RNN/LSTM layers, each with 50 units, followed by dropout layers with a rate of 0.2 to prevent overfitting by randomly dropping 20% of the neurons during training. The final layer was a dense layer with a single unit to output the prediction.

The model was compiled using the mean squared error (MSE) loss function and the Adam optimizer, with mean absolute error (MAE) as an additional performance metric.

The model was trained on the training dataset for 100 epochs with a batch size of 1, and a validation split of 20% was used to monitor the model's performance on unseen data during training.

E. Performance Metrics

Two of the most well-known metrics were used to evaluate the performance of the different forecasting models: Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

MAE focuses on the average magnitude of the errors between predicted and actual values. It calculates the absolute difference for each prediction, regardless of whether it's an overestimation or underestimation, and then averages them across all data points. A lower MAE indicates a model with predictions that are, on average, closer to the actual values. [9]

RMSE builds upon MAE by acknowledging that larger errors are more concerning. It squares the errors before averaging, giving more weight to significant discrepancies. Finally, the square root is taken to return the units to the original scale. A lower RMSE suggests the model is making smaller errors on average and can capture both large and small fluctuations effectively [9].

By analysing the results based on these metrics together, we can get a well-rounded picture of how well the model captures the central tendency of the data, the magnitude of errors, and their relative significance for different data points.

IV. Results

Based on the experiments, ARIMA resulted in high error rates on both Online and Offline Sales predictions indicating that it wasn't able to handle the complexity of the data effectively. Fig. 10 and Fig. 11 show the plots demonstrating the comparison between the predicted and the actual values.

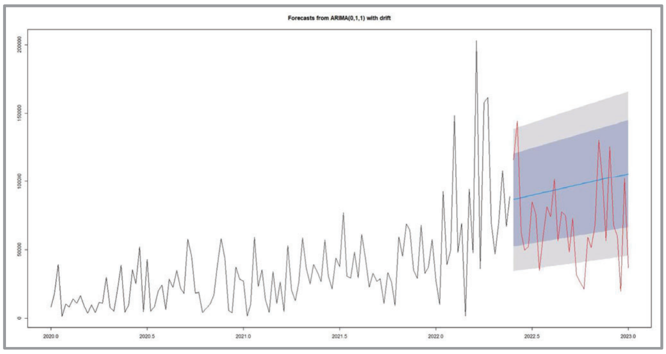

Fig. 10 ARIMA(0,1,1) (Online Sales Prediction)

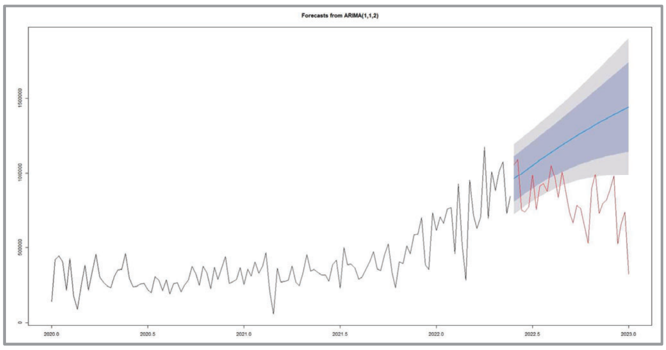

Fig. 11 ARIMA (0,1,1) (Offline Sales Prediction)

SARIMA performed better by incorporating seasonal components. Fig. 12 and Fig. 13 show the plots of the prediction. It is noticeable however that the overall trend on the Offline Sales prediction is off. Facebook Prophet, even though it is a more robust model, shows significantly higher error rates on Online Sales predictions compared to the other models, suggesting it may not be as suitable for this type of data. It performs slightly better on Offline Sales predictions but still has relatively high error rates. Fig. 14 and Fig. 15 show the plot of Facebook Prophet's predictions.

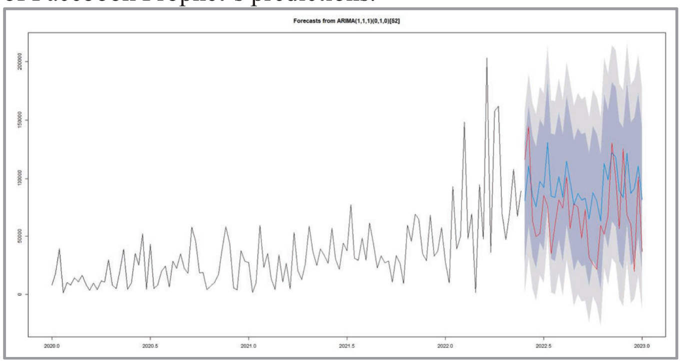

Fig. 12 ARIMA (1,1,1) (0,1,0) [52] (Online Sales Prediction)

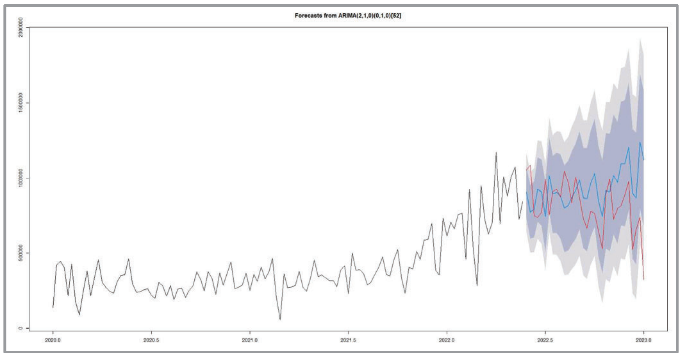

Fig. 13 ARIMA (2,1,0) (0,1,0) [52] (Offline Sales Prediction)

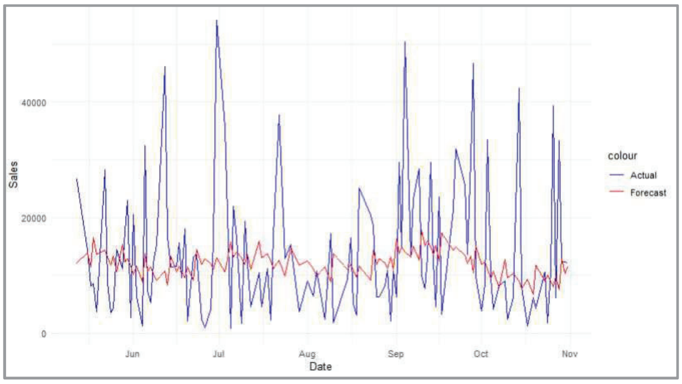

Fig. 14 Facebook Prophet (Offline Sales Prediction)

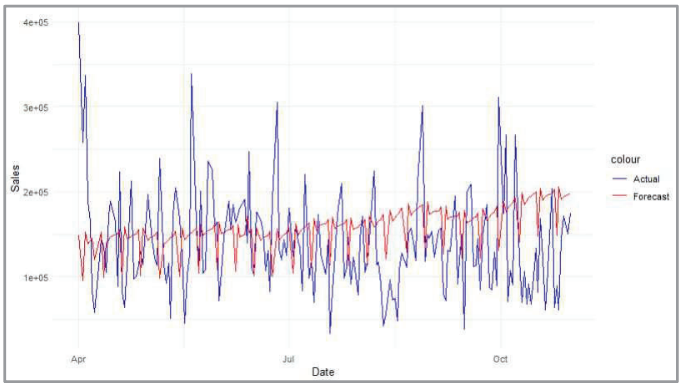

Fig. 15 Facebook Prophet (Offline Sales Prediction)

Neural network models Simple RNN and LSTM exhibited the best results. Specifically, the LSTM model achieves the lowest MAE and RMSE values, indicating its superior ability to comprehend the underlying patterns in the data. It is shown in Fig. 16 and Fig. 17 where not only the seasonality was evident, but the trend appears to be captured pretty accurately as well.

Table III and IV summarizes the results of all the forecasting models used in the study. Overall, in both Online and Offline Sales Forecasting scenarios, the neural network models Simple RNN and LSTM outperform the traditional time series models ARIMA and SARIMA and the Facebook Prophet forecasting tool. It is interesting to point out however that SARIMA had slightly better results than Simple RNN in the Offline Sales forecast. It may be because of the strong seasonality of Offline Sales that the SARIMA model was able to handle a bit better than Simple RNN, and also given that the data is relatively small.

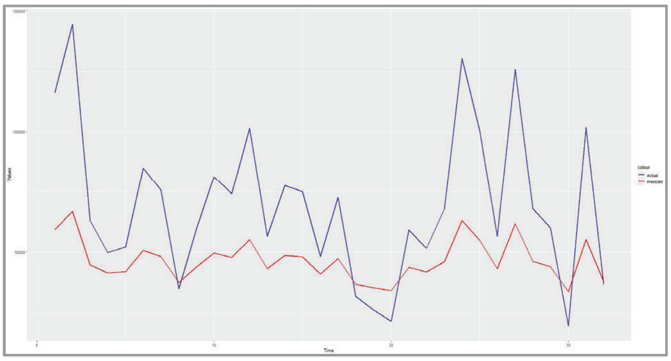

Fig. 16 LSTM (Online Sales Prediction)

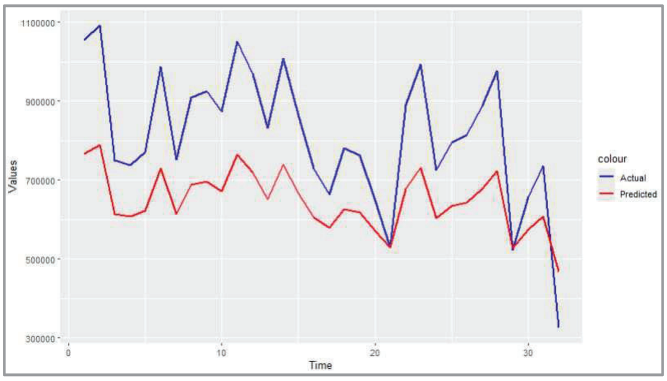

Fig. 17 LSTM (Offline Sales Prediction)

TABLE III PERFORMANCE METRICS (ONLINE SALES)

Model	MAE	RMSE
ARIMA	35924.33	42006.52
SARIMA	31011.62	36395.24
Facebook Prophet	59830.08	83430.20
Simple RNN	27740.90	34820.73
LSTM	**25640.67**	**32252.54**

TABLE IV PERFORMANCE METRICS (OFFLINE SALES)

Model	MAE	RMSE
ARIMA	418264.53	486119.20
SARIMA	201546.93	253751.10
Facebook Prophet	383630.24	481494.93
Simple RNN	233346.80	256960.86
LSTM	**173833.60**	**189996.16**

V. CONCLUSION

In conclusion, the evolution of techniques, driven by the advancements in technology, has significantly improved accuracy over time. This was demonstrated by the superior performance of LSTM over traditional approaches in this study. Newer methods like neural networks are emerging as powerful tools, particularly in sales forecasting, while established methods like ARIMA/SARIMA retain their relevance depending on the characteristics of the data and forecasting objectives. The integration of technology and diverse forecasting techniques offers a promising path towards more precise and effective predictions that are beneficial to businesses, not only in retail but also in other sectors.

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