Using time series analysis for sales and demand forecasting

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Problem Statement

Independent publishers often struggle to forecast book sales, affecting inventory, marketing, and title lifecycle decisions. Nielsen aims to provide accurate demand forecasts to support better planning. This project predicts weekly and monthly sales for *The Alchemist* and *The Very Hungry Caterpillar* (2012 onwards) using classical, machine learning, deep learning, and hybrid models, producing 32-week and 8-month forecasts to identify the most effective approach.

Summary of Approach

The analysis progressed through four stages. Weekly sales data were imported from Excel, covering all titles and associated fields. The data were filtered to retain the two target titles from 2012 onwards, dates were converted to datetime format, and missing weeks resampled to zero sales. Exploratory analysis visualised sales patterns, highlighting seasonality and trends. Five approaches were then applied: SARIMA, XGBoost, LSTM, SARIMA–LSTM hybrids, and monthly aggregation models. Performance was assessed on the final 32 weeks (weekly) and 8 months (monthly) using MAE and MAPE, with comparative plots generated. The results were then compared to determine the most effective model for each forecasting frequency.

Modelling and Results

This stage applied a range of forecasting methods in increasing order of model complexity: SARIMA, XGBoost, LSTM, SARIMA–LSTM hybrids, and monthly aggregation models. All were trained on data from 2012 onwards, with 32 weeks (weekly) or 8 months (monthly) reserved for testing. Performance was compared using MAE and MAPE, with results interpreted in the context of each model's strengths and limitations.

Classical Modelling (Weekly, SARIMA)

We initially attempted to apply Auto ARIMA to the weekly sales series, however this hit memory limitations. As a workaround, we conducted a manual SARIMA search, testing four candidate seasonal models for each book. Model parameters were guided by decomposition plots, ACF/PACF diagnostics, and the known seasonal period of 52 weeks.

Table 1 summarises the candidate models, including parameter configurations and information criteria. The best model for each title was selected based on the lowest AIC values, with residual diagnostics considered. Figures 1 and 2 show the chosen SARIMA model's forecasts for *The Alchemist* across the full historical period with a closer view of the final 100 weeks to highlight the forecast period. Table 2 reports the out-of-sample accuracy for each title over the final 32 weeks, with *The Alchemist* achieving a MAPE below 25%, indicating stronger accuracy than *The Very Hungry Caterpillar*.

Title	Model - (p,d,q)x(P,D,Q,52)	AIC	BIC	Ljung–Box p
The Alchemist	(0,1,1)x(1,1,0,52)	6401.5	6414.2	0.16
	(1,0,0)x(1,1,1,52)	6404.8	6421.8	0
	(1,0,1)x(1,1,1,52)	6361.6	6382.9	0.36
	(1,1,0)x(0,1,1,52)	6404.0	6416.7	0.19
The Very Hungry Caterpillar	(0,1,1)x(1,1,0,52)	7647.3	7660.0	0.77
	(1,0,0)x(1,1,1,52)	7575.2	7592.2	0.33
	(1,0,1)x(1,1,1,52)	7563.0	7584.2	0.75
	(1,1,0)x(0,1,1,52)	7597.3	7610.1	0.81

Table 1 Candidate SARIMA models for weekly forecasts.

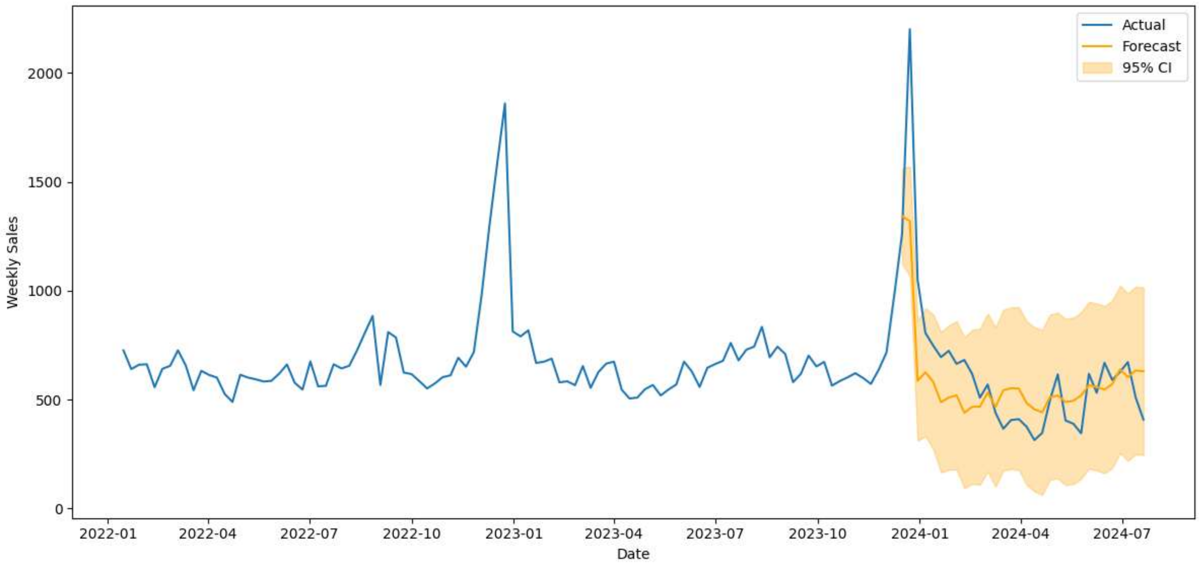

Figure 1 The Alchemist – Final 100 Weeks with Forecast vs Actual for SARIMA(1,0,1)(1,1,1,52) with 95% Confidence Intervals

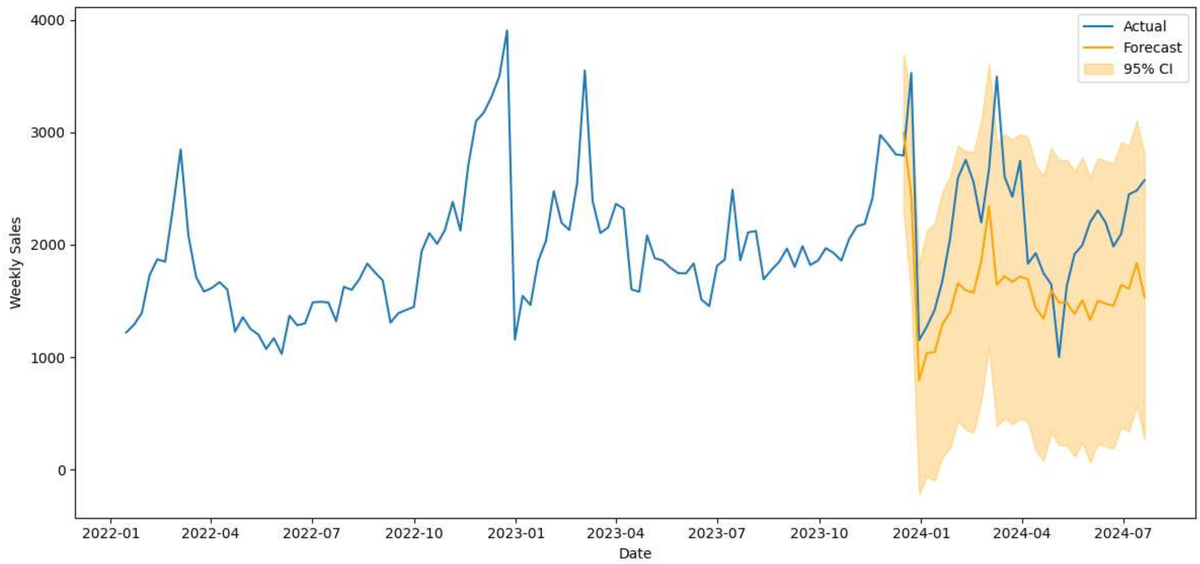

Figure 2 The Very Hungry Caterpillar – Final 100 Weeks with Forecast vs Actual for SARIMA(1,0,1)(1,1,1,52) with 95% Confidence Intervals

Title	MAE	MAPE (%)
The Alchemist	149.1	23.76
The Very Hungry Caterpillar	631.9	27.95

Table 2 Accuracy of selected SARIMA models on weekly forecasts

Machine Learning (XGBoost)

We implemented an XGBoost regressor using engineered lag features to capture short-term autocorrelation in the weekly sales series. Hyperparameters such as tree depth and learning rate were tuned via grid search with cross-validation.

Figure 3 shows the actual and predicted weekly sales for *The Alchemist* over the final 32 weeks, with the last 20 weeks of training data included to provide context. Figure 4 presents the equivalent plot for *The Very Hungry Caterpillar*.

Table 3 summarises predictive performance using MAE and MAPE on the test period.

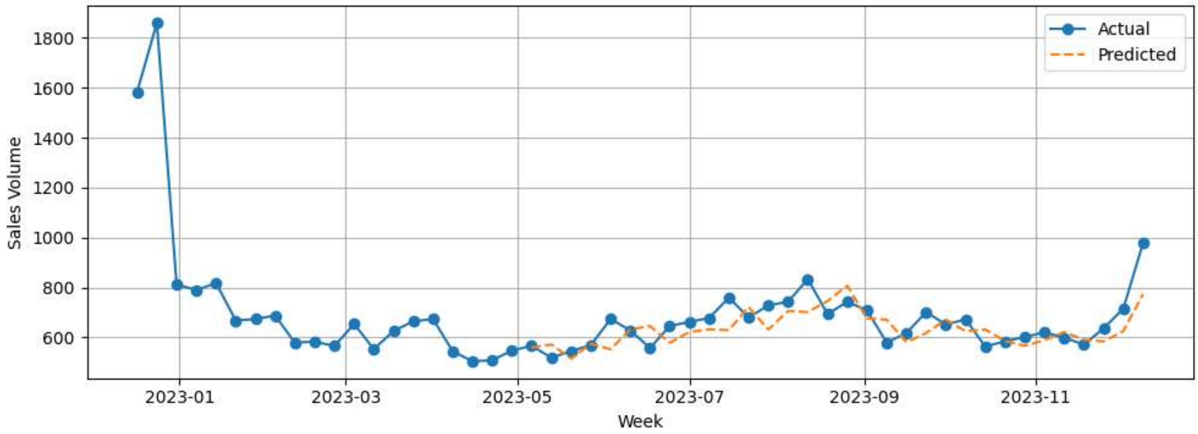

Figure 3 XGBoost forecast versus actual weekly sales for The Alchemist, showing the final 32 weeks of predictions with the last 20 weeks of training data for context.

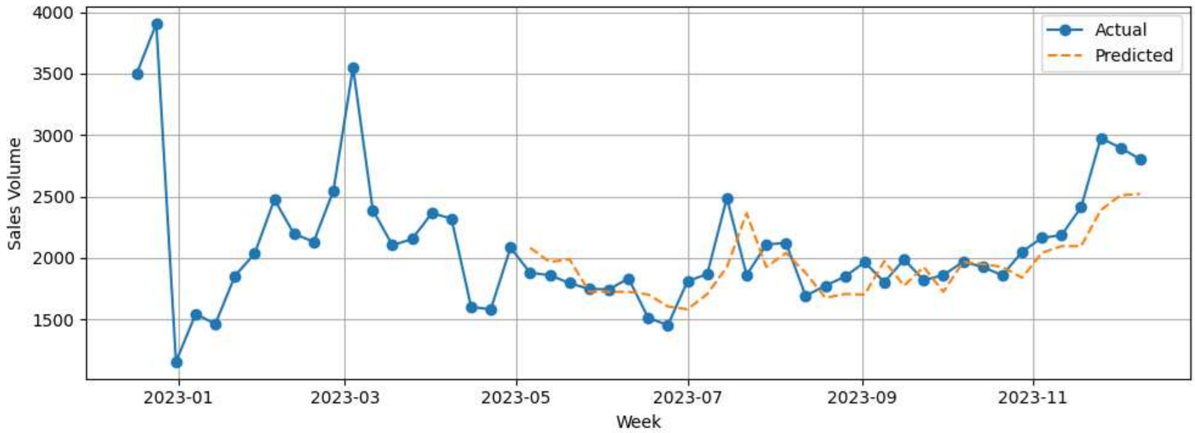

Figure 4 XGBoost forecast versus actual weekly sales for The Very Hungry Caterpillar, showing the final 32 weeks of predictions with the last 20 weeks of training data for context.

Title	MAE	MAPE (%)
The Alchemist	58.0	8.43
The Very Hungry Caterpillar	191.4	9.20

Table 3 Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) for XGBoost weekly forecasts on the test period for both titles.

Deep Learning (LSTM)

For each title, we implemented an LSTM model to capture sequential dependencies in the weekly sales data. Hyperparameters were tuned using KerasTuner, but the final forecasts showed a severe underfitting issue, with predictions remaining almost constant across the forecast period.

Figures 5 and 6 present the forecast versus actual sales for *The Alchemist* and *The Very Hungry Caterpillar* respectively. In both cases, the model failed to capture seasonal variation or short-term fluctuations, resulting in high error metrics (Table 4).

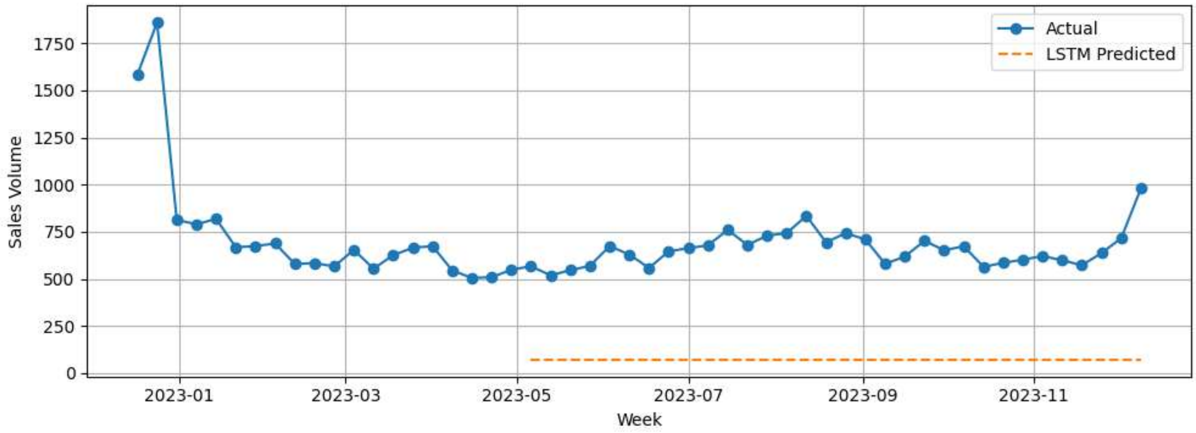

Figure 5 LSTM forecast versus actual weekly sales for The Alchemist, showing the final 32 weeks of predictions with the last 20 weeks of training data for context.

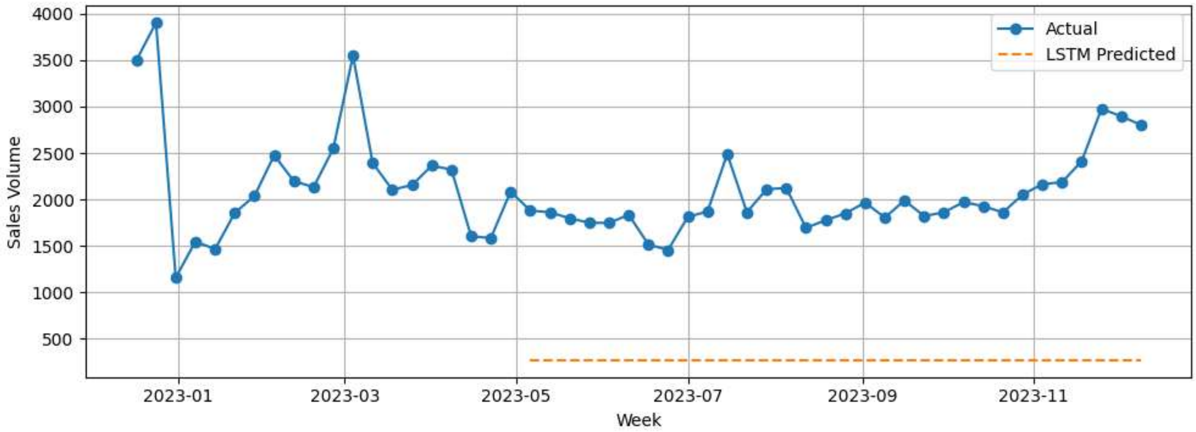

Figure 6 LSTM forecast versus actual weekly sales for The Very Hungry Caterpillar, showing the final 32 weeks of predictions with the last 20 weeks of training data for context.

Title	MAE	MAPE (%)
The Alchemist	586.1	88.94
The Very Hungry Caterpillar	1736.8	86.36

Table 4 Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) for LSTM weekly forecasts on the test period for both titles.

Hybrid Models (SARIMA + LSTM)

Two hybrid strategies were tested. In the sequential approach, SARIMA forecasts were generated first, with residuals modelled using an LSTM; the final forecast was the sum of both outputs. In the parallel approach, SARIMA and LSTM forecasts were produced independently and combined at a fixed 50:50 weighting. Figures 7 and 8 show sequential and parallel forecasts for *The Alchemist*, while Figures 9 and 10 show the equivalent for *The Very Hungry Caterpillar*. Weighted tuning of the parallel model assigned full weight to SARIMA, indicating the LSTM component did not improve accuracy in this configuration.

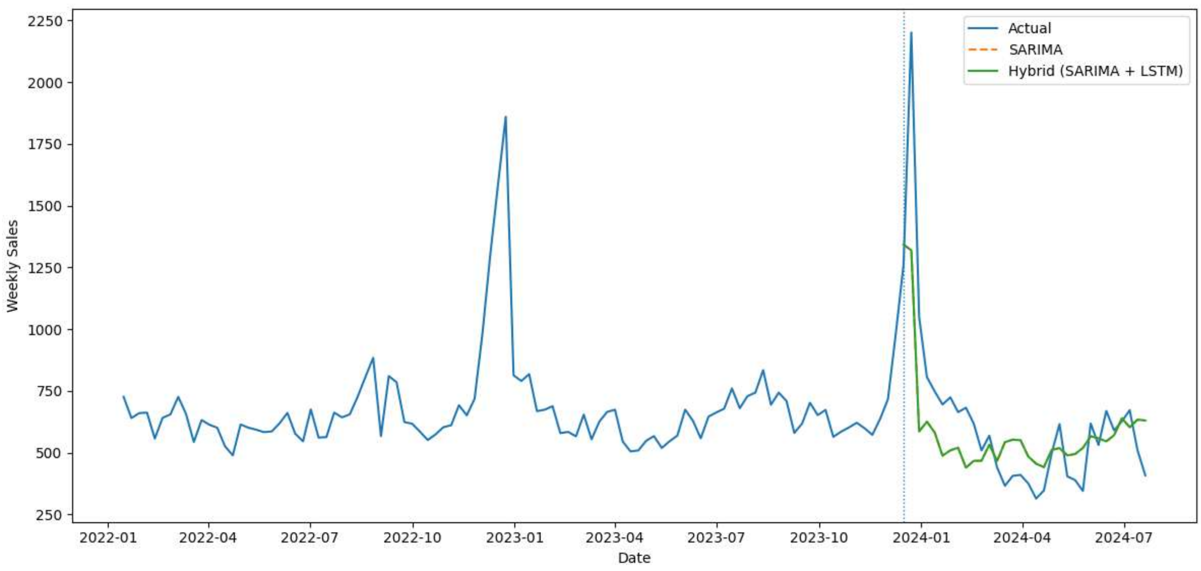

Figure 7 Sequential hybrid forecast for The Alchemist (final 32 weeks).

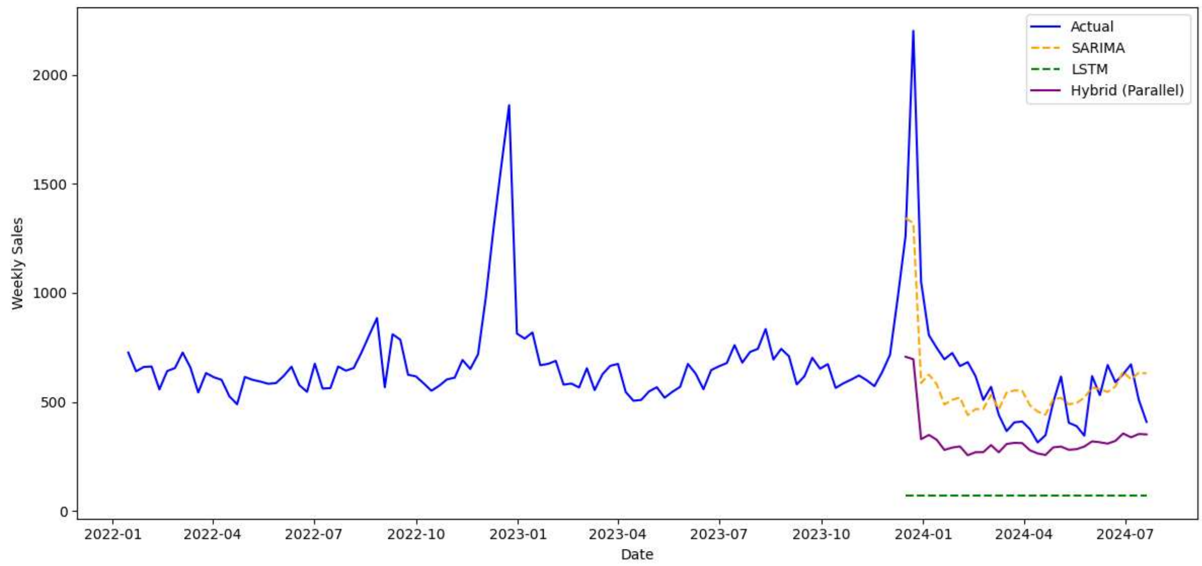

Figure 8 Parallel hybrid forecast for The Alchemist (final 32 weeks, 50:50 weighting).

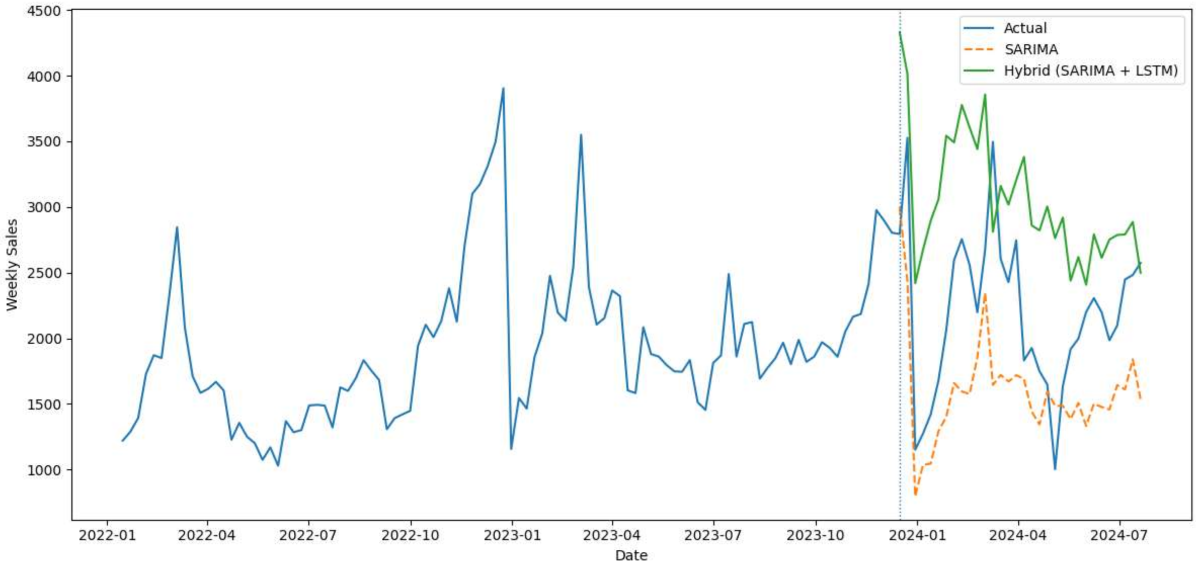

Figure 9 Sequential hybrid forecast for The Very Hungry Caterpillar (final 32 weeks).

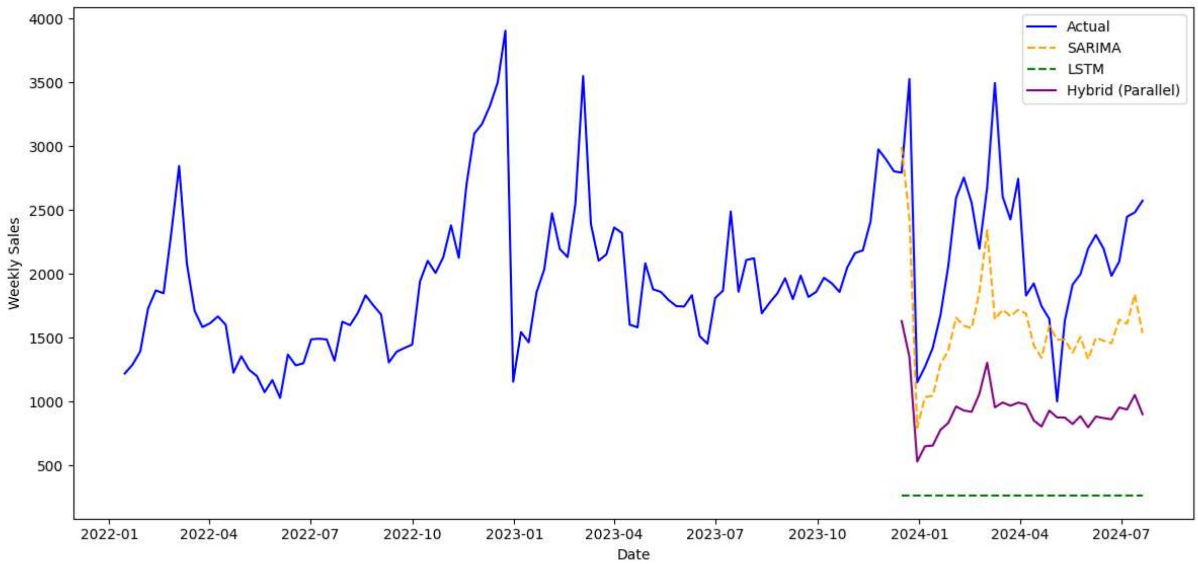

Figure 10 Parallel hybrid forecast for The Very Hungry Caterpillar (final 32 weeks, 50:50 weighting).

Monthly Forecasting

Weekly sales were aggregated to monthly totals for both titles, and two models were applied: an XGBoost regressor with lag-based features and a SARIMA model, with parameters selected using Auto ARIMA to account for monthly seasonality. Forecasts covered the final eight months of each series. Figures 11–14 show the XGBoost and SARIMA forecasts for both books, with forecast periods clearly marked.

Table 5 reports MAE and MAPE for both models before visual analysis, confirming XGBoost outperformed SARIMA for both titles. The gap was most pronounced for The Alchemist, where

SARIMA's MAPE was more than double XGBoost's, reflecting difficulty in modelling irregular monthly demand patterns.

Title	Model	MAE	MAPE (%)
The Alchemist	XGBoost	528.46	19.06
The Alchemist	SARIMA	1320.53	48.57
The Very Hungry Caterpillar	XGBoost	1909.33	22.6
The Very Hungry Caterpillar	SARIMA	2699.26	30.53

Table 5 MAE and MAPE for monthly forecasts produced by XGBoost and SARIMA for both titles.

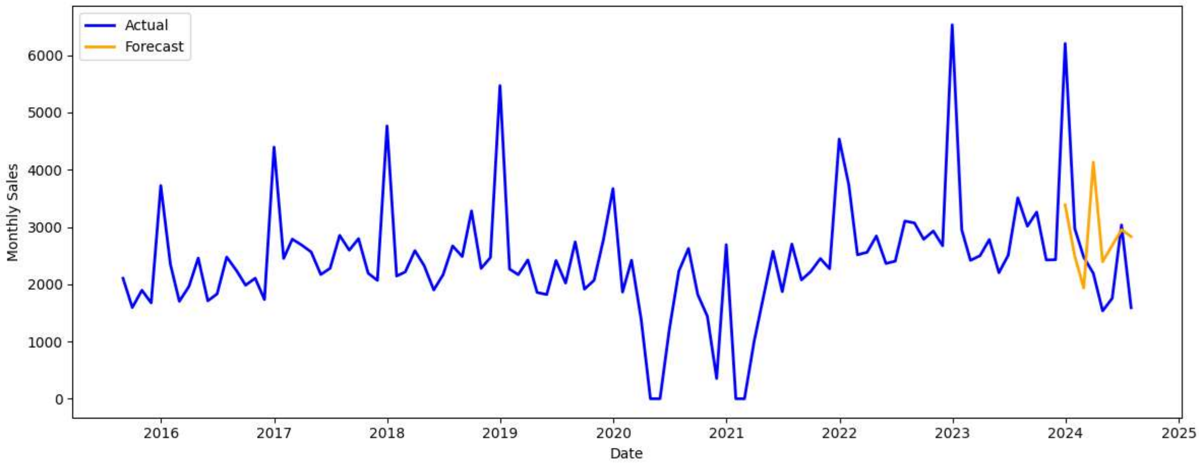

Figure 11 XGBoost monthly forecast vs actual sales for The Alchemist over the last 100 months.

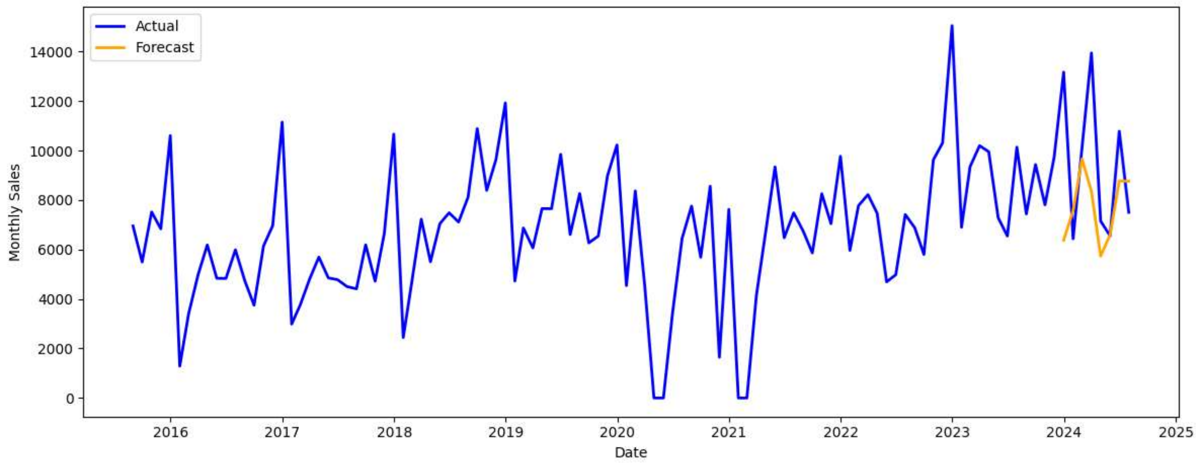

Figure 12 XGBoost monthly forecast vs actual sales for The Very Hungry Caterpillar over the last 100 months.

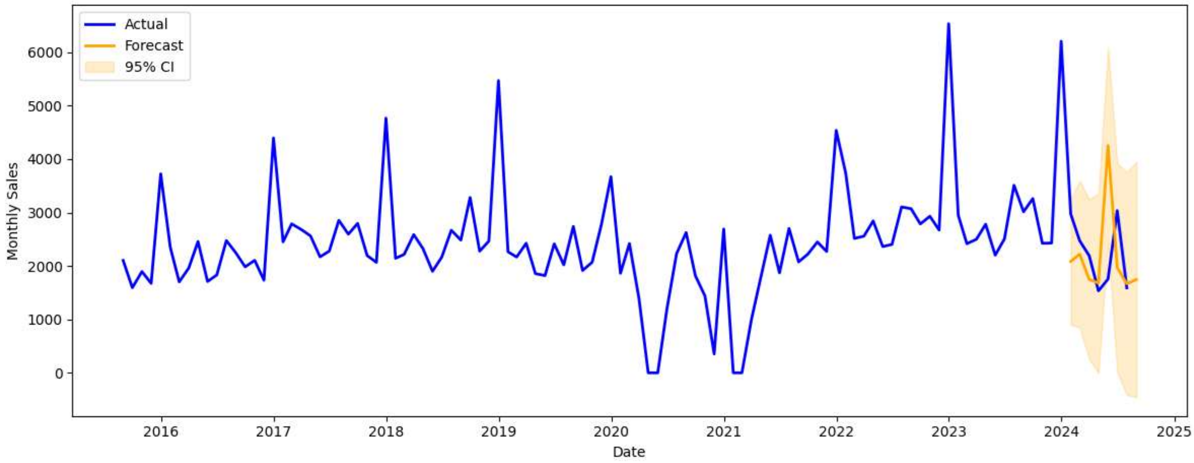

Figure 13 SARIMA monthly forecast vs actual sales for The Alchemist over the last 100 months, including 95% confidence intervals.

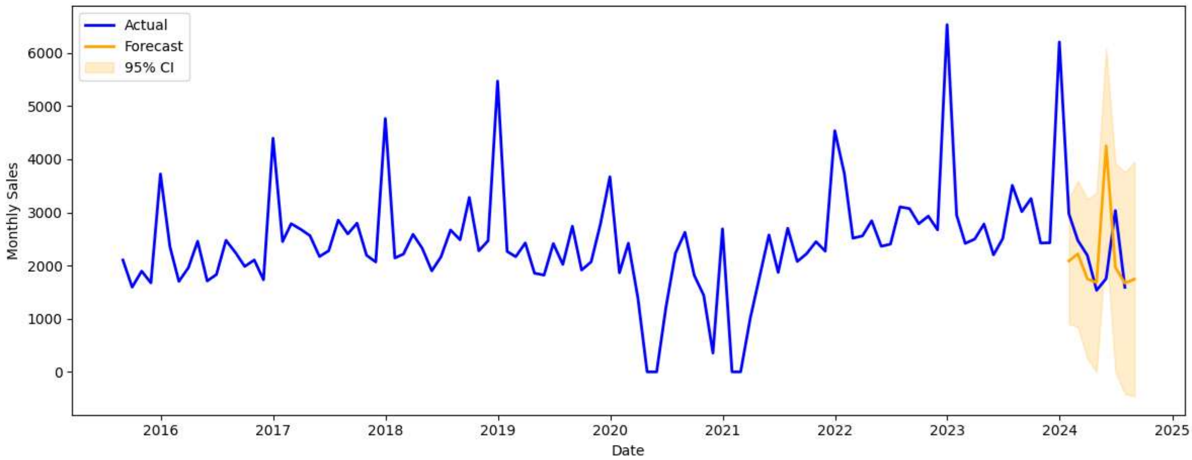

Figure 14 SARIMA monthly forecast vs actual sales for The Very Hungry Caterpillar over the last 100 months, including 95% confidence intervals.

Model Comparison and Selection

To compare the effectiveness of each approach, the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were calculated across all models for both weekly and monthly forecasts. Table 6 consolidates these results.

Model	Title	MAE	MAPE (%)
SARIMA (Weekly)	The Alchemist	149.10	23.76
	The Very Hungry Caterpillar	631.90	27.95
XGBoost (Weekly)	The Alchemist	58.00	8.43
	The Very Hungry Caterpillar	191.40	9.20
LSTM (Weekly)	The Alchemist	586.10	88.94
	The Very Hungry Caterpillar	1736.80	86.36
Hybrid – Sequential (Weekly)	The Alchemist	148.91	23.74
	The Very Hungry Caterpillar	2955.04	152.92
Hybrid – Parallel (Weekly)	The Alchemist	289.48	40.10
	The Very Hungry Caterpillar	1205.12	53.18
XGBoost (Monthly)	The Alchemist	528.46	19.06
	The Very Hungry Caterpillar	1909.33	22.60
SARIMA (Monthly)	The Alchemist	1320.53	48.57
	The Very Hungry Caterpillar	2699.26	30.53

Table 6 Comparison of Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) for all forecasting models applied to weekly and monthly sales of The Alchemist and The Very Hungry Caterpillar.

The results show that XGBoost achieved the lowest MAE and MAPE for both books in weekly forecasting, with particularly strong performance for *The Alchemist* (MAE 58.0, MAPE 8.43%). LSTM underperformed in both cases, with high error rates indicating limited suitability for the current dataset and configuration.

Hybrid models offered no clear advantage, with sequential and parallel combinations generally producing higher errors than their individual components. For monthly forecasting, XGBoost again outperformed SARIMA for both titles, with markedly lower error rates.

Based on these results, XGBoost emerges as the most effective approach for both weekly and monthly forecasts, offering high accuracy and stability across both datasets.

Conclusion

This project tested SARIMA, XGBoost, LSTM, and SARIMA–LSTM hybrids to forecast weekly and monthly sales for *The Alchemist* and *The Very Hungry Caterpillar* (2012 onwards), with monthly aggregation as an additional stage.

XGBoost delivered the lowest MAE and MAPE for both frequencies, excelling in weekly forecasts and outperforming all other models. LSTM performed poorly, while hybrids generally increased error rates. For monthly forecasts, XGBoost again surpassed SARIMA.

Auto ARIMA could not be run on weekly data due to memory limits, requiring manual SARIMA fitting, but was successfully applied to the aggregated monthly data to determine SARIMA parameters.

Overall, XGBoost provides a robust, accurate forecasting solution, offering publishers a reliable tool for sales planning, with scope for improvement through added features or external sources.