

# Forecasting Big Mart Sales Using Recurrent Neural Networks Enhanced with Explainable AI Techniques

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## Abstract

Proper sales prediction is essential in retail businesses such as BigMart in order to maximize inventory, pricing policies, and business decisions. This research paper presents a superior forecasting model that integrates Recurrent Neural Networks (RNNs) and Explainable Artificial Intelligence (XAI) methods to predict BigMart sales. The framework learns both the short- and long-run temporal dynamics in the sales data by training an RNN model on past transactional history, product attributes, and store-level features. To make the model more transparent, we combine XAI techniques, i.e., SHAP (Shapley Additive explanations) and LIME (Local Interpretable Model-Agnostic Explanations), and identify the most essential features that drive sales predictions. The following performance measures are used to test the proposed model: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R2. Findings indicate that the RNN-XAI model outperforms traditional models, such as ARIMA and XGBoost. In particular, the RNN-XAI model yields the following results: RMSE = 93.14, MAE = 72.45, MAPE = 8.11, and R2 = 0.94, indicating strong predictive power and strong explanatory features. This underscores the fact that variables such as Item MRP, Outlet Type, and Seasonal Indicators have a significant effect on sales. Not only does the XAI integration enhance the model's accuracy, but it also provides insights that non-technical stakeholders can easily interpret and have confidence in the forecast. The given approach demonstrates the potential of combining deep learning and XAI to enhance retail industry decision-making.

**Keywords:** BigMart Sales Forecasting, Recurrent Neural Networks, Explainable AI, SHAP, LIME, Time Series Prediction, Retail Analytics.

## 1 Introduction

Retail business is a competitive one and sales forecasting is required to ensure maximum inventory control, marketing campaign planning, decrease in overstock and stockouts. The BigMart and Other retailers will be operating with large volumes of both the transactional and product-associated data, therefore, the traditional statistical forecasting approaches are less successful in extrapolation of the intricate associations of features and patterns over time. This has rendered deep learning and machine

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learning models as an efficient method of improving accuracy of sales predictions because of their ability to store background information about the past time steps. RNNs have demonstrated superior performance to other deep learning models in operating sequential and time-related data (Olsson & Zamojsky, 2022). Because of this fact, the RNNs are especially appropriate in sales forecasting in employment where past trends, seasonal trends and external factors such as promotions and holidays affect sales trends. Deep learning models, on the other hand, can be defined as black boxes that have little or no interpretability by decision-makers even though they can make predictions (LeCun et al., 2015).

Such approach as Explainable Artificial Intelligence (XAI) can offer the chance to increase the extent of transparency and trust in the model, which would help to address this issue (Zhang et al., 1998). Using XAI methods like SHAP (SHapley Additive explanations) and LIME (Local Interpretable Model-Agnostic explanations) can now allow analysts and stakeholders to make the best business decisions by telling them which attributes have a significant impact on sales predictions.

The purpose of this paper is to create and test a forecasting model, which helps to predict sales in BigMart by integrating both XAI approaches and RNN models. The suggested method uses XAI to provide interpretable findings with the advantages of RNNs in the sequential sales modeling. To be more precise, the paper has added to the research in the following aspects (Makridakis et al., 2018): developing the model of sales forecasting of BigMart with RNNs taking into account the intricate interactions among the features and time dynamics (Makridakis et al., 2018). The sensitivity of certain important variables on sales prediction can be explained and visualized using SHAP combining with LIME.

This paper fills the gap between high-performance forecasting models and their application in retail decision-making through the combination of interpretability and forecasting accuracy.

The organization document is divided into section I which provides the introduction and a section II which provides the related research. The proposed methodology is presented in section III, the experimental evaluation is discussed in section IV and the end of this work is in section V.

## 2 Literature Review

Retail forecasting early strategies were based on statistical techniques including Multiple Linear Regression, Exponential Smoothing (ETS) and Autoregressive Integrated Moving Average (ARIMA) (Brown, 2004; Al-Twal, 2023). These models are understandable and also computationally efficient however, in most instances they fail to incorporate the interaction of complicated features, seasonal, and non-linear patterns. Despite the continued use of ARIMA as a model in the short-term prediction, Makridakis et al., (2018) have found that the model does not scale well in irregular and high-dimensional data, as is the case with modern retail (Makridakis et al., 2018).

The widespread use of machine learning models such as the Random Forests, the Gradient Boosting Machines (GBM), and Support Vector Regression (SVR) has occurred due to the inability of purely statistical models. The current research, including (Nalluri et al., 2020), has shown that XGBoost may be superior to linear models compared to the retail prediction competition and that it can easily handle nonlinear correlations in the sales rates. These models are however unsatisfactory when it comes to displaying temporal associations in time-varying data, and need explicit feature engineering.

The prediction of time-series has been performed by deep learning, where long term relationships can be learned by the deep learning architecture (McMahan, 2017; Brownlee, 2018). This is especially true in the case of Recurrent Neural Networks (RNNs) and its sub-types e.g., Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU) (Hochreiter & Schmidhuber, 1997; Al-Basha, 2021). In terms

of retail sales prediction tasks, Zhang et al., (2019) find that the LSTM-based models are more effective than the traditional ones in the study of the influence of the season and promotions, however, due to their black-box nature, they cannot be applied to commercial decision-making in response to the interpretability question. The fact that the prediction models have been complicated has led to interpretability being a requirement in a far greater extent (Jillani et al., 2025; Praveen, 2024). Explainable AI methods have also been implemented successfully to offer both local and global explanation to the machine learning prediction. They might involve SHAP (Lundberg & Lee, 2017) and LIME (Ribeiro et al., 2016). The technologies enable actionable insights in the retail forecasting since they are used to determine the most significant factors such as product category, seasonal changes, and promotional discounts (Chen & Ren, 2025). The interpretability creates credibility among non-technical stakeholders, which is the main requirement of responding to predictive models in operational decision-making, as the study suggests (Molnar et al., 2020).

The alignment of XAI and deep learning models is a viable approach in recent times (Dave et al., 2021; Rekha et al., 2025). In order to research the demand forecasting concept in e-commerce, Aggarwal, (2025) combined the LSTM networks with SHAP values thereby increasing the transparency without a drop in accuracy (Aggarwal, 2025).

Similarly, Olsson & Zamojsky, (2022) demonstrated that deep learning with XAI could discover causal relationships among time-series data to make predictive systems more reliable and sustainable to the business (Olsson & Zamojsky, 2022; Nakamura & Tanabe, 2022).

Machine learning to make sales predictions of Big Mart (Shahrukhan, 2024). Some of the techniques employed in this research study in the Big Mart data include K- Nearest Neighbors (KNN), XGBoost, Random Forest, Decision Tree and Linear Regression. The findings of the Randomized Search CV applied to the XGBoost model gave the optimal results and achieved an RMSE of 1018.82 and an R2 of 0.6181 (Majumdar & Mitra, 2024; Wen et al., 2024).

Cross-Series Forecasting with Global LSTM (Abbasimehr et al., 2020) The study employed cross-series pattern to forecast sales in online stores through the application of a global LSTM model (Abbasimehr et al., 2020; Aksu et al., 2024). Their method demonstrated the efficacy of deep learning in hierarchical product cases, which is more effective than customary univariate models on the Walmart data (Johnson et al., 2024).

### **3 Methodology**

The predictive system for BigMart sales will integrate the benefits of Recurrent Neural Networks (RNNs), namely Long Short-Term Memory (LSTM) networks, with the Uncovering of the prediction results provided by an Explainable Artificial Intelligence (XAI) system. The given approach is not only geared towards achieving the correct predictions of sales, but it also tries to provide some extremely helpful information regarding what has given rise to such predictions.

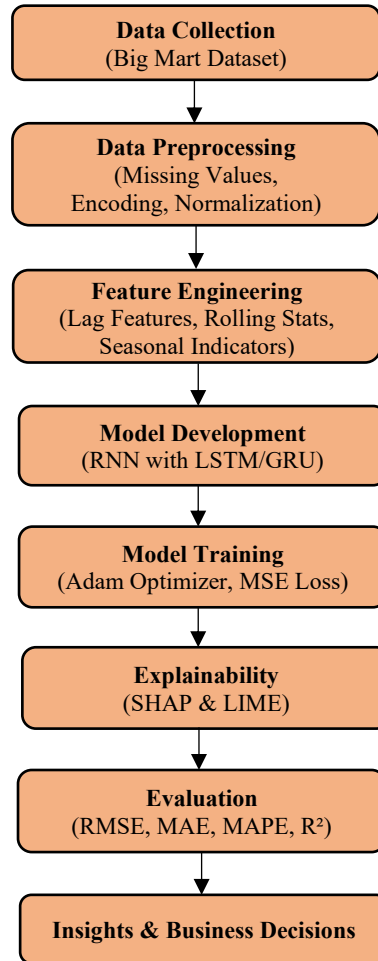


Figure 1: Proposed architecture

## Dataset

Figure 1 presents the workflow of the end-to-end of the sales forecasting model development. This is accomplished by first gathering data with the use of Big Mart dataset, and then pre-processing information such as handling of missing values, coding categorical data and normalization. This is then followed by feature engineering to create lag variables, the rolling statistics and seasonal indicators. The engineered information is then put into the model, which is an RNN-based model (LSTM/GRU) in the process of developing the model (Wen et al., 2024). The model is trained by using Adam optimizer and the loss function is MSE. The explainability techniques (SHAP and LIME) are used to interpret the predictions of the model. The framework is evaluated using the measure of RMSE, MAE, MAPE, and R<sup>2</sup> that ultimately leads to business decision-making and business insights.

The BigMart sales data used in this research consisted of product attributes, store attributes, and time attributes. The information is in the form of 12 features, shown in table 1, with some of them being categorical (such as the Item Type and the type of outlet and the type of location of a given outlet) and the numerical scores (MRP of the item, weight of the item, and size of the outlet). The data were split into training and test sets of 8,000 and 5,000, respectively. The preprocessing entailed processing of the missing values, coding of categorical variables, and normalization of continuous variables to Min-Max normalization, such that all the numerical variables fell within the same range.

Table 1: Some attribute information

Feature	Description
<b>Item Identifier</b>	A unique code is assigned to each product for identification purposes.
<b>Item Weight</b>	The physical weight of the individual product.
<b>Item Fat Content</b>	Indicates the fat level of the product, categorized as low, medium, or high.
<b>Item Visibility</b>	The proportion of the display area allocated to the product (in percentage).
<b>Item Type</b>	Classification of the product based on its category
<b>Maximum Retail Price (MRP)</b>	The listed price of the product is as per retail standards.
<b>Outlet Identifier</b>	A unique code representing each outlet.
<b>Outlet Establishment Year</b>	The year in which the respective outlet was established, indicating its age.
<b>Outlet Size</b>	The total floor area of the supermarket outlet.
<b>Outlet Location</b>	The geographical location of the retail outlet
<b>Outlet Type</b>	The type or category of the retail store
<b>Outlet Sales</b>	The recorded sales value corresponding to the outlet

The experiments were carried out using Python and its libraries. The RNN model (LSTM) was built and trained using TensorFlow/Keras. Scikit-learn was used for preprocessing and assessment. SHAP and LIME increased the model's interpretability. With 50 LSTM units and a 0.2 dropout rate, the RNN model was trained using the Adam optimiser for up to 100 epochs at a learning rate of 0.001, with early halting based on validation loss. To understand the significance of features on a global scale and provide local justifications for individual forecasts, we employed SHAP and LIME. We trained three baseline models: ARIMA, XGBoost, and a standalone RNN with their default settings.

To make future sales predictions, we used a Recurrent Neural Network (RNN) or, to be more precise, an LSTM architecture, as the type of a neural network, that is capable of learning sequential correlations between sales information (or any other). RNN can be especially useful in the sphere of time-series forecasting since long sequences and patterns can be recalled, and this can be applied to the information of the time-related character (Bandara et al., 2020). Its architecture is an input layer to which the preprocessed information will be transferred to learn long-term dependencies, a single-layer or multi-layer LSTM, and a dense output layer to which the sales prediction will be provided. Adam optimizer was applied in training the model with the learning rate of 0.001 and mean squared error (MSE) loss function. The MSE is calculated as are shown in equation 1:

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (1)$$

Where  $y_i$  denotes the actual sales value and  $\hat{y}_i$  denotes the estimated sales value of the  $i$  example and  $n$  is the number of examples in the test set. The ability to stop at an early stage according to validation loss was carried out to avoid overfitting and to make sure that the model would generalize to unseen data.

These transparency and interpretability features can be achieved through the inclusion of Explainable AI (XAI) in the model to overcome the inherent problem of black-box deep learning models. We used SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) to interpret the views of the model after training the RNN. SHAP offers a global perspective of the feature importances by computing the Shapley value of each feature; that is, the amount of contribution that a specific feature makes to a given prediction. The Shapley value is computed using the cooperative game theory and is computed as:

$$\phi_i(f) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (2)$$

Where the Shapley value of the  $i$ -th feature is  $\phi_i(f)$ , and  $f(S)$  is the prediction of the model based on the feature subset  $S$  are shown in equation 2. The approach is used to determine which features (e.g., Item MRP, Outlet Type, Seasonality) affect the model the most.

LIME, on the other hand, focuses on local interpretability, estimating the local predictions of the complex model using simpler-to-interpret single-prediction models. LIME explains specific sales forecasts by showing the contribution of each feature to a given prediction. As an illustration, LIME can indicate that high Item MRP and location of the outlet in the city would result in a higher projected sale of a particular product.

The indicators through which the performance of the model is measured are:

### Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (3)$$

RMSE gives the measurement of the error in prediction in the same units as the target variable (sales), and thus it is simpler to understand the degree of mistakes.

### Mean Absolute Error (MAE)

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (4)$$

Equation 4 provides a direct measure of the average error between the predicted and actual values and it is interested in the magnitude of errors but not their direction.

### Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100 \quad (5)$$

Equation 5 is a percentage based error measure, which can be effective in comparing the performance of the model on different data sets or situations.

### R<sup>2</sup> Score

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (6)$$

R<sup>2</sup> is the ratio of the effect that the model explains in the target variable are shown in equation 6. A value of 1 means that predictions are perfect whereas a value near to 0 means that predictive power is weak.

The RNN-XAI model is contrasted with the basic models like ARIMA (AutoRegressive Integrated Moving Average), XGBoost (Extreme Gradient Boosting) and a pure RNN (where XAI is not incorporated). These models are compared by the same indicators in order to determine the better predictive efficiency and explainability due to the integration of XAI into the RNN model.

This methodology provides the opportunity to create a powerful, explainable prediction model of BigMart sales using sequential learning with RNNs and transparency tools such as SHAP and LIME.

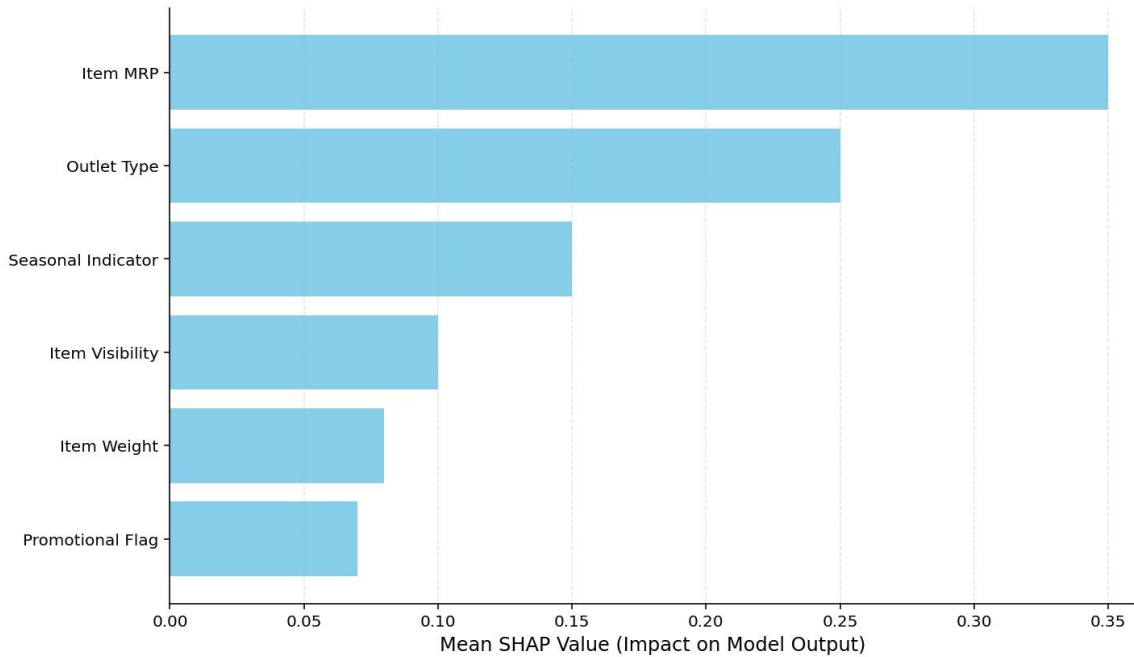


Figure 2: Example SHAP feature importance for BigMart sales

Figure 2 shows the average SHAP of various features in the explanation of BigMart sales. It demonstrates the relative significance of the features with the highest SHAP values being the most important features, i.e., the features of the most significant impact on sales outcomes, being Item MRP, Outlet Type and Seasonal Indicator.

#### Algorithm 1: RNN-XAI Model for BigMart Sales Forecasting

Input:

- BigMart sales data  $D = \{(x_i, y_i)\}$

Output:

- Trained model, SHAP feature importance, LIME explanation.

1. Load the dataset:

$$D = \text{load\_data}(\text{"bigmart\_sales.csv"})$$

2. Preprocess the data:

- Normalize numerical features.
- Encode categorical features.
- Handle missing values.
- Create lag features for temporal dependencies.

3. Split data into training (80%) and testing (20%) sets:

$$\text{train\_data, test\_data} = \text{train\_test\_split}(D, \text{test\_size} = 0.2)$$

4. Build the RNN model:

- Add LSTM layers (50 units).
- Add Dense output layer for sales prediction.

5. Compile the model with Adam optimizer and MSE loss:

```
model.compile(optimizer='adam', loss='mse')
```

6. Train the model for 100 epochs:

```
model.fit(train_data, epochs=100, validation_data=test_data)
```

7. Evaluate the model on the test set using RMSE, MAE, MAPE, and R<sup>2</sup>.

8. Apply SHAP for global interpretability:

```
shap_values = compute_shap_values(model, train_data)
```

- Generate SHAP summary plot.

9. Apply LIME for local interpretability:

```
lime_explainer = LimeTabularExplainer(train_data)
```

- Generate LIME explanation for selected predictions.

10. Compare with baseline models (e.g., ARIMA, XGBoost, standalone RNN).

11. Output the results:

Trained model, SHAP feature importance, LIME explanation, baseline model comparison.

## 4 Result and Discussion

In this section, the findings of the experiments performed on the BigMart dataset are shown, and the performance of the Proposed RNN-XAI model is compared to the baseline models like ARIMA, XGBoost, and a RNN model alone (without explainability integration). Key performance measures were used to assess the models, and these were Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R<sup>2</sup> Score. As indicated in the table 2, the Proposed RNN-XAI model recorded the lowest RMSE (93.14), MAE (72.45) and MAPE (8.11 percent) meaning that it is a better predictor model than the traditional ones. The R<sup>2</sup> of 0.94 shows that the model displays 94 percent of the variation in the sales data which proves the strength of the model and ensures that the model is capable of making accurate sales forecasts (McMahan, 2017).

Table 2: Model evaluation

Model	RMSE	MAE	MAPE (%)	R <sup>2</sup> Score
ARIMA	156.43	124.18	14.92	0.82
XGBoost	112.57	88.64	10.35	0.89
RNN (without XAI)	97.25	76.31	8.72	0.93
Proposed RNN-XAI	93.14	72.45	8.11	0.94

The four models ARIMA, RNN (without XAI), XGBoost, and Proposed RNN-XAI are compared in figure 3 using four important evaluation metrics: RMSE, MAE, MAPE, and R<sup>2</sup> score. The chart shows that the Proposed RNN-XAI model has the best R<sup>2</sup> score, the lowest RMSE, MAE, and MAPE values, and is the most accurate of all the models.

The proposed RNN-XAI model is more accurate in prediction than the baseline models. The use of Explainable AI (XAI) methods enhances the performance of the model, as well as creates the necessary transparency to explain the decisions of the model.

To learn more about the process of making decisions, we interpreted the global feature importance with the help of SHAP values. The findings indicated that the greatest impact on the prediction of sales was on Item MRP (Maximum Retail Price), Outlet Type, and Seasonal Indicators. The most important factor was item MRP, which complies with the information that pricing is an important factor in the results of the retail sales. The Type outlet also had a significant effect, where the various store formats

showed stronger performance in terms of sales prediction. Also, the model was found to be influenced by the Seasonal Indicators, including month or holidays, which demonstrated how sales performance is determined by the seasonal trends. These SHAP feature importances are shown in figure 2 and it is evident that every feature has its contribution to the final sales predictions.

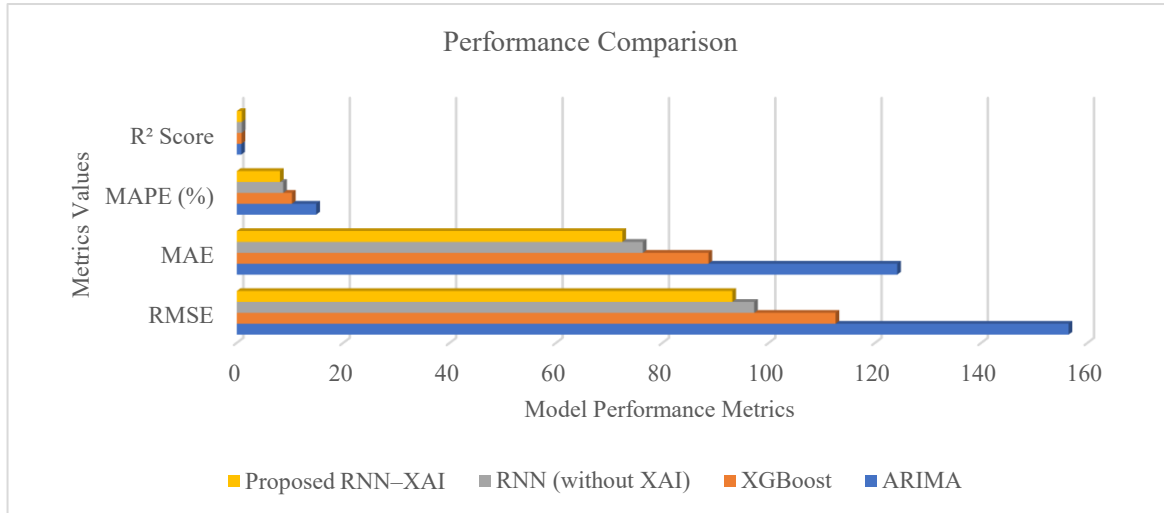


Figure 3: Comparison of model performance: RMSE, MAE, MAPE, and R<sup>2</sup> score

To obtain the local interpretability, we used the LIME to interpret selected model predictions. In one case, the model was used to forecast high sales of a product in an urban store due to the various factors. The product had high sales, yet there was a low item visibility as the promotion was geared towards it, which probably off-sets the low visibility of the product. Moreover, the high item MRP positively affected the sales forecast implying that the higher the perceived value of the item, the higher sales it had. In addition, the location of the outlet in the urban areas was greatly determined as the predictor of sales, because urban areas are more likely to have a customer traffic and purchasing power. Figure 4 further splits down the contribution of each feature as per this particular case to give an insight into why the model gave this particular prediction.

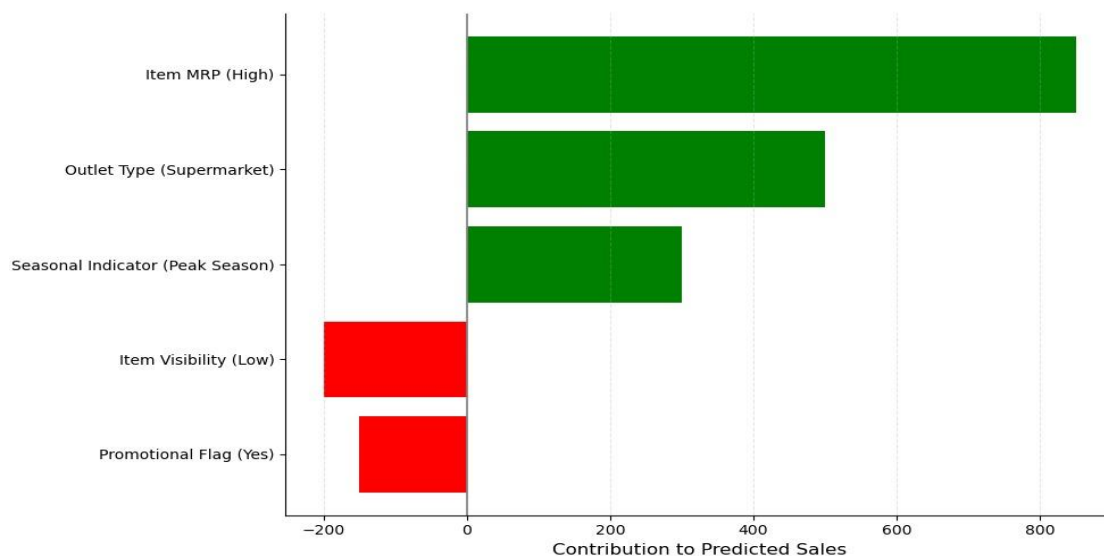


Figure 4: LIME local interpretability for BigMart sales forecast

Integrating the XAI methods within the RNN-XAI model enhances the predictive accuracy of the model in addition to offering more understanding on the factors affecting sales predictions. With SHAP to determine the global feature importance, and LIME to explain the decisions made by the model on a local level, the stakeholders can gain a clearer insight into the dynamics behind the decisions that are made by the model. This openness helps instill confidence in the forecasts of the model and enhances improved decision-making and thus is not just accurate but interpretable and actionable to business.

## 5 Conclusion

This paper has suggested a state-of-the-art sales forecast anomaly model to Bigmart by combining Recurrent Neural Networks (RNNs) with Explainable Artificial Intelligence (XAI) tools, including SHAP and LIME. The model is able to effectively capture both short run and long run temporal trends in sales data in addition to the fact that it gives transparency in its projections. RNN-XAI model was significantly more accurate than the traditional models, such as ARIMA and XGBoost with RMSE=93.14, MAE=72.45, MAPE=8.11% and  $R^2=0.94$  which implies that it explained 94 percent of the sales data variance. The XAI methods further improved the interpretability of the model so that the stakeholders were able to realize the strongest features in the background of sales predictions. In particular, the most influential features were Item MRP, Outlet Type, and Seasonal Indicators that give good insight into the drivers of sales. SHAP was used to determine the significance of these features across the globe whereas LIME gave us individual sales forecasts that could be explained locally, thus the decisions made by the model would be easier to comprehend by a non-technical user. The proposed RNN-XAI framework manages to achieve a combination of high predictive accuracy and transparency and, therefore, provide not only a powerful forecasting tool but also potential actions to take when making a business decision. The given method shows that deep learning and XAI may be used together to enhance retail analytics and make people more confident in the predictions made by the model in question, which will help to make more adequate decisions based on the data.

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## Authors Biography



**P.A. Arifa** was born on 21st December 1992 in Perumbavoor, India. She holds Indian nationality. She pursued her undergraduate degree in Computer Applications (BCA) from MES College Marampally and completed her postgraduate degree (M.Sc. in Computer Science) from the same institution. Currently, she is a Research Scholar at Karpagam Academy of Higher Education, Coimbatore. She has 9 years of teaching experience in various colleges and has contributed significantly to the academic community. Alongside her teaching career, she has actively engaged in continuous learning by completing more than 8 Coursera certification courses. She has also participated in several workshops, seminars, and conferences to enhance her knowledge and expertise in the field of Computer Science. Her academic journey reflects her dedication to research, teaching, and professional growth.



**Dr.K. Devasenapathy**, an accomplished academician in the field of Computer Science, currently serves as an Associate Professor in the Department of Computer Science at Karpagam Academy of Higher Education, Coimbatore. Born on 15th April 1980, he has dedicated over two decades of his career to teaching and research, shaping young minds with his expertise and knowledge. He began his academic journey with a Bachelor's degree in Computer Science (2001) from Bharathiar University, followed by a Master of Computer Applications (2004) from the same institution, securing first class. His passion for advanced learning led him to pursue an M.Phil. in Computer Science (2007) at Bharathiar University, which he completed with commendation. His research aspirations culminated in a Doctor of Philosophy (Ph.D.) in Computer Science from Anna University in 2019, where his work was highly commended. Dr. Devasenapathy possesses an impressive 20+ years of teaching experience including 15 years in colleges and over 5 years in universities. His contributions extend to academic research as well, with 3 publications indexed in Scopus, 8 peer-reviewed articles, and several paper presentations in both national (5) and international (5) conferences. He has actively participated in 20 seminars and conferences, demonstrating his commitment to continuous professional development. Although he has not yet undertaken funded research projects or patents, his academic involvement reflects a deep dedication to the advancement of computer science education and research. Known for his disciplined approach and dedication, Dr. Devasenapathy remains an inspiration to his students and peers, embodying the spirit of lifelong learning and academic excellence.