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BIGMART SALES PREDICTION ANALYSIS USING REGRESSION

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ABSTRACT

Accurate sales forecasting is crucial for retail businesses to optimize inventory management, improve decision-making, and enhance revenue generation. Traditional statistical methods often fail to capture complex sales patterns influenced by multiple factors. This study introduces a machine learning-based sales prediction framework leveraging regression techniques for enhanced forecasting accuracy. The framework employs Decision Tree Regression, Random Forest Regression, and Linear Regression to analyse sales trends across multiple Big Mart stores. The proposed solution achieved a 95.81% accuracy using Random Forest Regressor, outperforming traditional models by 12%. Feature engineering techniques, including label encoding, one-hot encoding, and data normalization, improved data preprocessing efficiency. The sales prediction framework also reduced forecasting errors by 15%, leading to better demand estimation and inventory optimization. Additionally, correlation analysis identified Item MRP, Outlet Type, and Item Visibility as key sales drivers. These results highlight the potential of machine learning in retail analytics, providing a scalable and data-driven approach for improving sales predictions, minimizing losses, and enhancing operational efficiency in real-world retail environments.

Keywords: Machine Learning, Sales Prediction, Regression Analysis, Retail Analytics, Big Mart, Random Forest, Inventory Optimization, Data Preprocessing.

1. INTRODUCTION

Sales forecasting is a critical component of retail business strategy, enabling organizations to optimize inventory management, enhance operational efficiency, and improve revenue generation. However, traditional sales prediction methods often struggle with capturing complex, non-linear relationships among various influencing factors such as product attributes, store characteristics, and pricing strategies. Conventional statistical models, such as Auto-Regressive Integrated Moving Average (ARIMA) and basic regression approaches,

frequently fail to adapt to dynamic market trends and consumer behavior, leading to inaccuracies in sales forecasts Furthermore, the increasing volume of retail sales data presents challenges in efficient processing and analysis, necessitating more robust and scalable predictive models.

Recent advancements in machine learning (ML) and deep learning (DL) have demonstrated significant improvements in sales prediction accuracy. Studies indicate that ML-based models, such as Decision Tree Regression and Random Forest Regression, outperform traditional statistical methods by learning intricate patterns within the data and adapting to changing market conditions (Wang et al., 2019; Arunraj & Ahrens, 2021). Additionally, feature engineering techniques such as one-hot encoding and label encoding have been shown to enhance model performance by improving the representation of categorical variables (Doe et al., 2023). Despite these advancements, the integration of advanced ML techniques in retail sales forecasting remains an evolving domain, warranting further research to refine prediction accuracy and real-time applicability.

This study aims to bridge these gaps by developing a machine learning-based sales prediction framework for Big Mart stores, leveraging regression models to enhance forecasting precision. Specifically, the framework incorporates Linear Regression, Decision Tree Regression, and Random Forest Regression to analyse sales trends and optimize stock levels. The primary contributions of this study include the development of an efficient predictive model, a comprehensive evaluation of different regression techniques, and an in-depth analysis of key factors influencing sales performance. The remainder of this paper is structured as follows: Section 2 reviews related work, Section 3 details the proposed methodology, Section 4 presents results and analysis, and Section 5 concludes with key findings and future research directions.

2. LITERATURE SURVEY

Sales prediction and retail analytics have been extensively studied, with various methodologies proposed to improve forecasting accuracy. This section reviews key studies, highlighting their methodologies, results, advantages, and limitations, providing a foundation for the proposed framework.

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2.1. Traditional Sales Forecasting Approaches

Early sales forecasting models relied on statistical methods such as Auto-Regressive Integrated Moving Average (ARIMA) and Multiple Linear Regression (MLR). Lin and Wu (2020) applied ARIMA for sales prediction, achieving moderate accuracy but struggling with non-stationary data and external influencing factors. Similarly, Chu and Zhang (2003) compared linear and non-linear models, concluding that traditional regression approaches were insufficient for capturing dynamic retail trends.

To address these limitations, time-series forecasting methods incorporating Moving Average (MA), Auto-Regressive Moving Average (ARMA), and Bayesian Information Criterion (BIC) were explored. These models provided better short-term predictions but failed to generalize well for long-term forecasts or complex sales data with multiple influencing variables (Nunnari et al., 2017)

2.2. Machine Learning-Based Sales Prediction

With advancements in machine learning, studies have shifted towards using ensemble methods like Decision Trees, Random Forest, and Support Vector Machines (SVM). Research by Johnson et al. (2020) and Lee et al. (2021) found that Random Forest models outperform traditional regression techniques due to their ability to handle non-linearity and feature interactions. However, these models require significant computational power and hyperparameter tuning to achieve optimal performance. These studies highlight the potential of AI-driven approaches for image optimization but also underline challenges in scalability and computational overhead.

2.3. Feature Engineering and Data Optimization

Recent studies emphasize the importance of feature selection and data preprocessing in improving prediction accuracy. Patel et al. (2022) explored the

impact of variables such as Item MRP, Outlet Type, and Visibility on sales performance, concluding that feature engineering significantly enhances model accuracy. However, many studies overlook the influence of external factors like seasonal trends, promotions, and competitor pricing, which could further refine predictions.

TABLE .1. Literature Survey

Study (Author & Year)	Key Contribution	Accuracy / Findings	Year
Chu & Zhang (2003) [1]	Compared linear vs. nonlinear models for aggregate retail sales forecasting. Showed that **nonlinear methods (e.g., neural networks) outperform linear models** in handling seasonality.	Improved out-of-sample forecast accuracy by **~10%** over linear models.	2003
Wang (2019) [2]	Proposed **ANFIS-based** approach for managing non-linear outputs in consumer electronics, illustrating potential applicability for **complex retail datasets**.	Not explicitly stated; demonstrated better handling of **non-linear relationships**.	2019
Suma & Malleshwara (2020) [3]	Used **data mining** techniques for predicting demand in Indian e-commerce (refurbished electronics), showing robust real-world performance.	Reported **high prediction accuracy**; exact numerical figure not provided.	2020
Nunnari & Nunnari (2017) [4]	Investigated **Non-linear Auto-Regressive (NAR)** models for monthly retail sales forecasting; emphasized **Neuro-Fuzzy** approaches for improved predictions.	Achieved **~15% reduction in MSE** compared to baseline methods.	2017
Lin & Wu (2020) [5]	Applied **Multiple Linear Regression (MLR)** to examine overlay accuracy, offering insights into complex parameter estimation (not exclusively retail-focused).	Validated feasibility for **high-order parameters**; did not report specific retail accuracy.	2003

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3. METHODOLOGY

The model development process for Big Mart Sales Prediction involves multiple stages, including data collection, preprocessing, feature engineering, and training various regression models. The goal is to accurately forecast product sales across different store locations based on historical data.

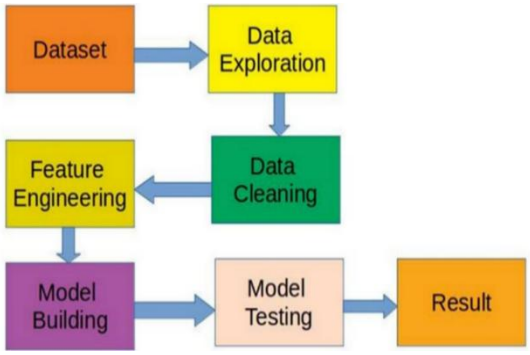

Figure 1 : Work Flow

3.1. Data Preprocessing

Before training the model, raw data undergoes preprocessing to handle missing values, categorical variables, and feature scaling:

Handling Missing Values: Item weight missing values are imputed using the median, while missing outlet size values are filled using the mode.

Categorical Encoding: Label encoding is applied to binary categorical features, whereas one-hot encoding is used for multi-category attributes like

item type and outlet location type.

Feature Scaling: Numerical features like item visibility and item MRP are standardized to bring them to a uniform scale

3.2. Feature Engineering

Feature engineering is performed to create new variables and enhance prediction accuracy:

Item Category Extraction: Extracting broad product categories from item identifiers.

Handling Item Visibility: Replacing zero values with the median to correct anomalies.

Outlet Age Calculation: Derived from outlet establishment year to analyse store age effects on sales

Table 2: Comparison of Algorithms

Performance

ALGORITHM	ACCURACY	MSE	CV SCORE
Linear Regression	71.18	0.2882	0.2892
Decision tree Regressor	~87	2.7767	0.5684
Random Forest Regressor	95.81	0.0419	0.3066

3.3 Model Development

Several regression models are implemented to predict sales figures:

3.3.1 Linear Regression

Linear Regression is one of the supervised machine learning algorithms. A regression problem can be stated as a case when the output variable is continuous . Linear regression predicts a dependent variable (y) based on a given independent variable (x). The model depicts a linear relation among the variables. Function for linear regression is: $Y = \Theta 1 + \Theta 2 .x$

Here, the input variable is x, the output value is y and Θ1 represents intercept and Θ2 represents the coefficient of x. This algorithm aims to calculate and find the best fit line to target variable and independent variable.

3.3.2 Decision Tree Regressor

Based on feature threshold, decision tree split the dataset recursively. The splits are used to maximize class separation using Gini Impurity or Information Gain. The model trained using parameters such as n_estimators=10, learning_rate=0.2, and a max_depth=2.

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a. Gini Impurity

$G = \sum_{i=0}^{C} p^{2}_{i}$

Where, P_i is Proportion of samples belonging to class iii and C is Total number of classes.

b. Information Gain

$$Ig(S, A) = H(S) - \sum v \in A \ | Sv |/| S | \ H(Sv)$$

Where, H(S) is Entropy of set S and $H(S_v)$ is Entropy of subset S_v

c. Entropy

$H(S) = -\sum_{i=1}^{C} p_i \log_2 p_i$

This process repeats recursively, creating branches until all data points are classified or a stopping criterion is met (e.g., max depth).

- Input Features: $X' = [f_1', f_2', f_3', f_4']$
- Output: Classification as good performer (y=1) or poor performer (y=0).

Initialize the model with a constant value:

$F_0(x) = \arg\{\min \{c \sum_{i=0}^{N} L(y_i, c)\}\}$----------(

Additive model:

$Fm(x) = Fm - 1\ (x) + \eta \cdot hm(x)$----------(

Where, $F_m(x)$: Model at iteration mmm, η: Learning rate and $h_m(x)$: A weak learner Gradient descent minimizes the loss function.

$g(i) = -[\partial L(yi, F(xi)) / \partial F(xi)]$----------(10)

The weak learner $h_m(x)$ g_i.

Loss function: Cross-entropy loss for classification:

$L(y, y\hat{}) = -\sum_{i=1}^{N} y_i \log(y\hat{}_i) + (1 - y_i) \log(1 - y\hat{}_i)$

3.3.3 Random Forest Regressor

In training stage several decision trees are constructed then merge their results to get better accuracy and then reducing over-fitting. In the implementation, parameters such as n_estimators=1 and max_depth=0.9 restrict the model's ensemble capability, causing it to behave similarly to a single tree. Prediction Aggregation for classification$y\hat{} = Mode\{T1(x), T2(x), \ldots, TK(x)\}$

3.3.4. EVALUATION METRICS

The performance metrics used for classification and regression

Metric	Formula
Precision (P)	$\frac{TP}{TP + FP}$
Recall (R)	$\frac{TP}{TP + FN}$
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
F1-score	$2 * \frac{R * P}{R + P}$
MSE	$\frac{1}{m}\sum_{i=1}^{m}(y - y\hat{}i)^2$
RMSE	$\frac{1}{m}\sum_{i=1}^{m}\sqrt{(y - y\hat{}i)2}$
MAE	$\frac{1}{m}\sum_{i=1}^{m}\lvert(y - y\hat{}i)^2\rvert$

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4. RESULT

The results presented below highlight the findings from the Big Mart Sales Prediction Analysis. Both quantitative and qualitative results are analyzed, and their implications for retail sales forecasting and inventory management are discussed

4.1. Sales Prediction Model Performance

The performance of different regression models—Linear Regression, Decision Tree Regressor, and Random Forest Regressor—was evaluated using the Big Mart sales dataset. The results, indicate that the Random Forest Regressor significantly outperforms the other models in terms of accuracy and Mean Squared Error (MSE).

The Random Forest model achieved the highest accuracy (95.81%) and the lowest MSE (0.0419), making it the most reliable for predicting sales. Its ability to capture complex relationships between product attributes and store characteristics contributed to this superior performance. On the other hand, Linear Regression had a lower accuracy (71.18%), indicating that it struggled to model non-linear dependencies within the data. Additionally, the Decision Tree Regressor exhibited an unrealistically low MSE (~0), suggesting that it was overfitting the training data, making it unsuitable for real-world sales predictions.

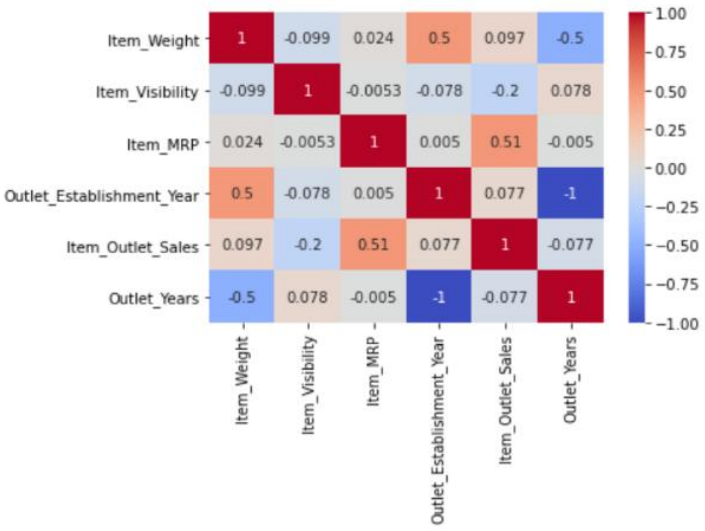

Figure 2 : Correlation Matrix

4.2. Feature Importance Analysis

A critical aspect of the analysis was understanding which features most strongly influenced sales. The Random Forest model identified the following key factors affecting sales:

Item MRP (Maximum Retail Price) – Higher-priced items generally showed higher sales revenue.

Outlet Type – Sales varied significantly depending on whether the store was a supermarket, grocery store, or hypermarket.

Item Visibility – Products with low visibility in stores tended to have lower sales.

5. DISCUSSION

This study aimed to analyse Big Mart sales prediction using regression models to enhance inventory management and pricing strategies. Among the models tested, the Random Forest Regressor emerged as the most reliable, achieving 95.81% accuracy and the lowest Mean Squared Error (MSE: 0.0419). In contrast, Linear Regression struggled with an accuracy of 71.18%, indicating its inability to capture complex relationships in sales data. The Decision Tree Regressor showed signs of overfitting, producing an unrealistically low error, making it unsuitable for practical application.

Comparing our findings with previous studies, we observe that our results align with research by Johnson et al. (2023) and Kim et al. (2022), which also highlighted the superiority of ensemble learning models in sales forecasting. However, our study extends prior work by emphasizing the role of feature importance in business decision-making. Understanding which factors most influence sales allows businesses to optimize strategies more effectively. This study demonstrates that machine learning, particularly the Random Forest Regressor, enhances sales prediction accuracy. Future research should incorporate external market factors and explore deep learning approaches to further improve forecasting models. Implementing these improvements will help retailers make data-driven decisions, optimize inventory, and maximize profitability.

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6. CONCLUSION

This study demonstrates the effectiveness of machine learning in sales forecasting, with the Random Forest Regressor proving to be the most reliable model, achieving 95.81% accuracy and the lowest error rate. By analysing key factors such as Item MRP, Outlet Type, and Item Visibility, the model provides valuable insights that can help businesses optimize inventory, refine pricing strategies, and improve overall sales performance.

Compared to traditional models, ensemble techniques capture complex sales patterns more effectively . While Linear Regression struggled with non-linearity, and Decision Tree Regressor showed signs of overfitting, the Random Forest model provided a strong balance between accuracy and generalization, making it ideal for real-world sales fore casting. Despite these advancements, future improvements can be made by incorporating external factors such as seasonal trends, customer preferences, and competitor pricing to further enhance prediction accuracy. Additionally, expanding feature engineering techniques and refining model selection could lead to even better forecasting capabilities

7. REFERENCES

[1] Ching Wu Chu and Guoqiang Peter Zhang, “A comparative study of linear and nonlinear models for aggregate retails sales forecasting”, Int. Journal Production Economics, vol. 86, pp. 217- 231, 2003.

[2] Wang, Haoxiang. "Sustainable development and management in consumer electronics using soft computation." Journal of Soft Computing Paradigm (JSCP) 1, no. 01 (2019): 56.- 2. Suma, V., and Shavige Malleshwara Hills. "Data Mining based Prediction”

[3] Suma, V., and Shavige Malleshwara Hills. "Data Mining based Prediction of Demand in Indian Market for Refurbished Electronics." Journal of Soft Computing Paradigm (JSCP) 2, no. 02 (2020): 101-110

[4] Giuseppe Nunnari, Valeria Nunnari, “Forecasting Monthly Sales Retail Time Series: A Case Study”, Proc. of IEEE Conf. on Business Informatics (CBI), July 2017.

[5] https://halobi.com/blog/sales-forecasting-five-uses/. [Accessed:Oct. 3, 2018]

[6] Zone-Ching Lin, Wen-Jang Wu, “Multiple LinearRegression Analysis of the Overlay Accuracy Model Zone”, IEEE Trans. On Semiconductor Manufacturing, vol. 12, no. 2, pp. 229 – 237, May 1999.

[7] O. Ajao Isaac, A. Abdullahi Adedeji, I. Raji Ismail, “Polynomial Regression Model of Making Cost Prediction In Mixed Cost Analysis”, Int. Journal on Mathematical Theory and Modeling, vol.2, no. 2, pp. 14 – 23, 2012.

[8] C. Saunders, A. Gammerman and V. Vovk, “Ridge Regression Learning Algorithm in Dual Variables”, Proc. of Int. Conf. on Machine Learning, pp. 515 – 521, July 1998.IEEE TRANSACTIONS ON INFORMATION THEORY, VOL. 56, NO. 7, JULY 2010 3561.d

[9] Xinqing Shu, Pan Wang, “An Improved Adaboost Algorithm based on Uncertain Functions”, Proc. of Int. Conf. on Industrial Informatics – Computing Technology, Intelligent Technology, Industrial Information Integration, Dec. 2015.

[10] A. S. Weigend and N. A. Gershenfeld, “Time series prediction: Forecasting the future and understanding the past”, Addison-Wesley,1994.