Real-time Research Project/ Societal Related Project
on

SALES PREDICTION FOR FURNITURE SOFA

Submitted in partial fulfillment of the requirements
for the award of degree of

BACHELOR OF TECHNOLOGY
in
Information Technology
by

Ms.R.Harini (22WH1A1250)
Ms.N.Joy Beulah (22WH1A1223)
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Under the esteemed guidance of
Mr.A.Rajashekar Reddy
Assistant Professor

VISHNU
UNIVERSAL LEARNING
BVRIT H
Estd. 2012

Department of Information Technology
BVRIT HYDERABAD College of Engineering for Women
(UGC Autonomous Institution | Approved by AICTE | Affiliated to JNTUH)
(NAAC Accredited - A Grade | NBA Accredited B.Tech. (EEE, ECE, CSE & IT))
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Department of Information Technology

CERTIFICATE

This is to certify that the Project report on **" Sales Prediction For Furniture Sofa"** is a bonafide work carried out by **Ms.R.Harini (22WH1A1250), Ms.N.Joy Beulah (22WH1A1223) and Ms.D.Harshini (22WH1A1224)** in the partial fulfillment for the award of B.Tech degree in **Information Technology, BVRIT HYDERABAD College of Engineering for Women, Bachupally, Hyderabad** affiliated to Jawaharlal Nehru Technological University, Hyderabad, under my guidance and supervision. The results embodied in the project work have not been submitted to any other university or institute for the award of any degree or diploma.

Internal Guidance	**Head of Department**
Mr.A.Rajashekar Reddy	**Dr.Aruna Rao S.L**
Assistant Professor	**Professor and HOD**
Department of IT	**Department of IT**

DECLARATION

We hereby declare that the work presented in this project entitled **" SALES PREDICTION FOR FURNITURE SOFA"** submitted towards completion of in II year II sem of B.Tech IT at "BVRIT HYDERABAD College of Engineering for Women", Hyderabad is an authentic record of our original work carried out under the esteemed guidance of **Mr.A.Rajashekar Reddy, Assistant Professor**, Department of Information Technology.

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This project report is dedicated to my beloved Family members and supervisor for their limitless support and encouragement and to you as a reader

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ABSTRACT

Sales prediction for furniture sofas is vital for optimizing supply chains, inventory management, and strategic planning in retail. This project leverages advanced machine learning techniques to forecast sofa sales by analyzing historical data and seasonal trends. After sourcing comprehensive data and extensive preprocessing, we employed Microsoft Azure to develop various regression models. The boosted decision tree regression model emerged as the most effective in capturing complex feature interactions. Key factors influencing sales include ratings, dimensions, price, and warranty. The model's high accuracy supports decision-making for customers,manufacturers, and supply chain managers,enhancing production plan, stock control, and marketing strategies.

Our findings reveal that value-for-money and quality are top customer priorities leading to increased sales for well-rated and longer-warranty products.predictive model enhances efficiency, customer satisfaction, and sustainable practices in the furniture industry.

Keywords: Sales Prediction, Machine Learning, Furniture Industry

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Chapter 1

Introduction

1.1 Introduction

This project emphasizes the development of a predictive model for sofa sales, leveraging machine learning techniques to analyze historical data and identify seasonal trends.By integrating advanced data preprocessing and regression models, the aim is to provide precise sales forecasts that will benefit various stakeholders in the furniture industry, including customers, manufacturers, and supply chain managers.

1.2 Motivation

The motivation for this sales prediction project comes from the need for better accuracy in forecasting sales in the furniture industry, especially for managing inventory and planning production. Traditional methods often find it challenging to handle the unpredictable demand and complex consumer preferences. This project uses machine learning techniques to improve forecasting, offering more reliable insights for managing stock and aligning making with market needs. The goal is to boost operational efficiency and support better decision-making, helping to match demand forecasts with actual sales.

1.3 Objectives

The key objectives include creating a robust machine learning model to forecast sofa sales, examining the impact of factors like dimensions, ratings,warranty and price.providing insights to refine inventory and marketing strategies, ultimately aiming to improve sales forecasting accuracy and offer actionable recommendations for optimizing business operations.

1.4 Scope

Sales prediction for furniture sofas involves a comprehensive approach that starts with gathering detailed data from the WoodenStreet website, including 255 records and 11 features related to sofa sales. The project includes meticulous data pre processing to ensure quality and consistency, with steps like normalization, parsing, and imputation. Following data preparation, various regression models developed and trained using Microsoft Azure, aiming to identify the model with the highest accuracy for forecasting sales. Although the focus is on sofa sales, methodologies and insights are adaptable to other product categories and industries, enhancing the project's applicability and helping improve inventory management, production planning, and strategic decision-making.

1.5 Contributions

This project contributes by delivering a predictive model with high accuracy for forecasting sofa sales, offering valuable insights into sales-driving factors. It supports better decision-making in inventory management and marketing strategies, ultimately promoting efficiency and sustainability within the furniture industry.

1.6 Organization

The report covers methodology, design, implementation and results, providing a comprehensive overview of the project's processes and findings. It includes visualizations and performance metrics to support the analysis. The report offers clear insights into the model's development and application. It reflects the project's outcomes and impact.

Chapter 2

Literature Survey

It delve's into the practical applications of Azure Machine Learning, illustrating how it can be effectively utilized for developing, training, and deploying machine learning models. The authors provide detailed, step-by-step instructions for setting up the Azure environment, managing large datasets, and optimizing models to improve performance. The guide also highlights the importance of implementing MLOps practices, which help in maintaining model accuracy, facilitating continuous improvement, and ensuring operational consistency. MLOps, a set of practices that combines machine learning (ML) and DevOps, is crucial for automating the end-to-end machine learning lifecycle, including model versioning, testing, deployment, simplifies the model selection and hyperparameter tuning process, and the use of Azure's powerful machine learning compute clusters that can handle high-performance training tasks. It provides practical insights into building a resilient machine learning infrastructure, ensuring that models can be deployed efficiently and maintained effectively over time. [1]

Here we explore the intersection of data mining and deep learning to enhance the prediction of merchandise sales on e-commerce platforms. The research integrates a variety of machine learning algorithms, such as neural networks and decision trees, to analyze extensive datasets that influence sales performance. The study demonstrates how combining traditional data mining techniques with state-of-the-art deep learning models can significantly improve prediction accuracy. The paper also discusses the importance of real-time data processing and the ability to update models dynamically as new data becomes available. By applying these techniques to real world ecommerce data, illustrate the potential for advanced analytics to drive business decisions and optimize sales strategies. This paper is a crucial read for those looking to understand how sophisticated analytical methods can be employed to forecast sales in the highly competitive and data-rich e-commerce sector, providing a roadmap for implementing similar approaches in other industries.[2]

Introducing an innovative adaptive machine learning model tailored for predicting sales at Walmart, addressing the complexities of fluctuating sales patterns and seasonal trends. The study emphasizes the necessity of adaptive algorithms that can adjust predictions based on real-time data inputs, thereby enhancing the model's responsiveness and accuracy. By comparing various machine learning techniques, the authors highlight the superiority of their adaptive model in managing the dynamic nature of retail sales. The research includes a thorough analysis of historical sales data, seasonal adjustments, and trend detection, showcasing how these factors can be integrated into a predictive framework. This work not only advances the understanding of adaptive learning in retail but also provides a practical implementation strategy that can be replicated across different retail environments to improve sales forecasting reliability.[3]

They offer an in-depth examination of the critical role of seasonality and trend detection in enhancing the accuracy of predictive sales forecasting. The study focuses on the challenges of identifying and adjusting for seasonal variations and long-term trends, which are often significant factors in sales data. Using a variety of machine learning techniques, demonstrates how incorporating these elements into predictive models can substantially improve forecast precision. The paper provides detailed methodologies for analyzing seasonal patterns, detecting trends, and integrating these findings into machine learning algorithms. By presenting case studies and empirical evidence, illustrates the practical applications and benefits of this approach, making a strong case for its adoption in industries with pronounced seasonal demand fluctuations. This research is particularly relevant for businesses looking to refine their sales forecasting methods and achieve more reliable predictions in environments where demand patterns are influenced by seasonal and trend-based factors.[4]

Chapter 3

System Design

3.1 System Optimization

The System design process involved several key components to ensure effective and accurate predictions

3.1.1 Phase 1: Feature Selection

Critical features such as price, dimensions, ratings, and warranty were selected based on their relevance to sales predictions. This step involved assessing the impact of each feature on sales performance.

3.1.2 Phase 2: Data Enrichment

Data was enriched by integrating supplementary sources, including market trends and customer demographics. Missing values were imputed to maintain data integrity. This enhanced dataset provided a more robust foundation for accurate predictions.

3.1.3 Phase 3: Model Evaluation

Various regression models, including linear regression, decision forests, Poisson regression, and boosted decision trees, were evaluated. Performance was assessed based on accuracy and computational efficiency.

3.1.4 Phase 4: Model Optimization

Hyperparameters tuning was conducted using grid search and randomized search techniques. Cross-validation was employed to validate model performance and prevent overfitting, ensuring generalizability.

3.1.5 Phase 5: Performance Metrics

Models were evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared values. The boosted decision tree model was selected for its superior performance and accuracy in capturing complex patterns in the data.

3.2 Associated Technologies

3.2.1 Python

Python is used for scripting and data processing, with Pandas handling data cleaning to ensure accurate inputs for the model. Its extensive libraries streamline tasks from data manipulation to model development.

3.2.2 Selenium

Selenium automates browser interactions, managing window tabs and extracting data from multiple web sources efficiently. It enhances data collection by automating repetitive tasks.

3.2.3 Microsoft Azure

Microsoft Azure offers cloud-based infrastructure for data pipelines and model deployment, providing scalable resources for real-time processing and integration. It supports efficient data management and model operations.

3.2.4 Postman API

Postman API tests and validates the deployed model's endpoint, ensuring correct functionality and integration. Its automated features help with ongoing API validation and troubleshooting.

Chapter 4

Methodology

4.1 Data Acquisition

We collected data from WoodenStreet by employing advanced web scraping techniques by selenium. This approach allowed us to gather 11 features and 255 records from the WoodenStreet website by switching the window tabs, capturing essential features like price, dimensions, and ratings.

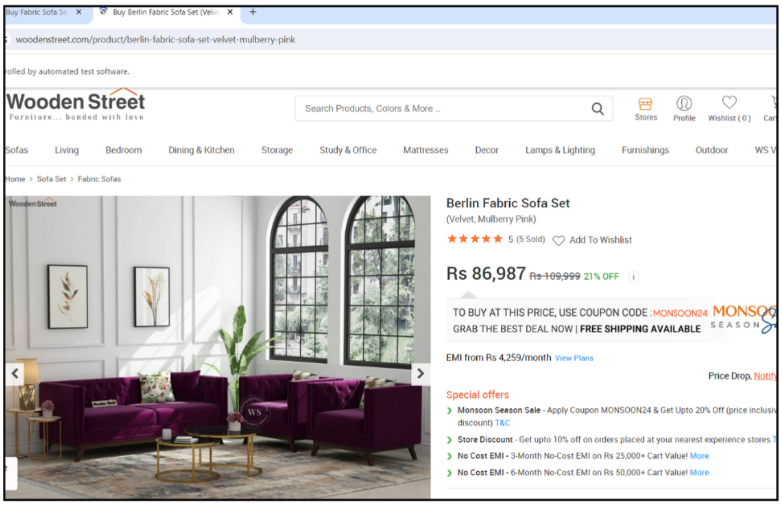

Figure 4.1: Website HomePage

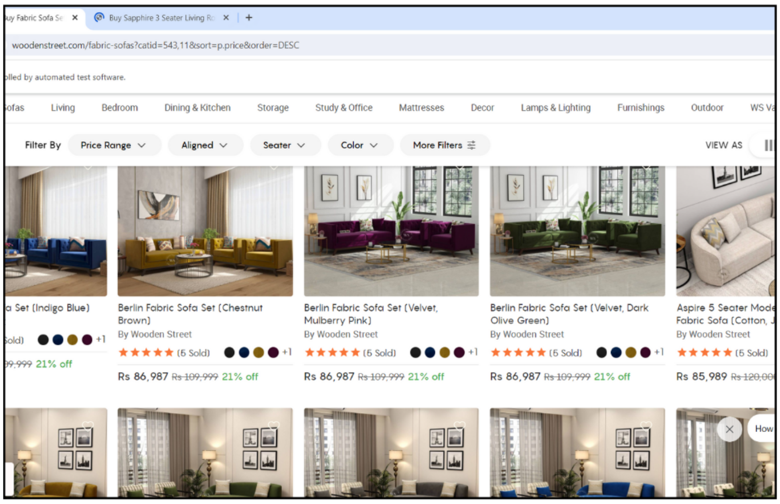

Figure 4.2: Homepage

4.2 Data Cleaning and Preparation

The data cleaning process involved several critical steps to ensure accuracy and consistency:

- Price Normalization: Standardized price formats to facilitate comparison.
- Whitespace Trimming: Removed extraneous spaces from text fields.
- Dimension Parsing: Extracted and structured dimension data for uniformity.
- Integer Extraction: Converted relevant data points into integer values.
- Missing Data Imputation: Addressed and filled in any missing data points.

All processed data was consolidated into a single CSV file, creating a clean and comprehensive dataset ready for analysis. This dataset included normalized prices, parsed dimensions, and ratings, and accounted for warranties. We also performed feature scaling and encoding to ensure compatibility with various machine learning algorithms. The resulting dataset was then used for exploratory data analysis (EDA) to uncover patterns and correlations, which guided further refinement of the model.

Price	Designs	Material	Color	Warranty	Brand	Length (Cn	Breadth (C	Height (Cn	Ratings	Sold Coun
125988	Modern	Cotton	Red	36	Wooden S	309.9	81.3	73.7	4.5	27
125988	Modern	Cotton	Blue	36	Wooden S	309.9	81.3	73.7	4.5	27
122989	Modern	Velvet	Green	36	Wooden S	309.9	81.3	73.7	4.5	27
119999	Modern	Leatherett	Grey	36	Wooden S	269.7	99.3	66.8	5	15
92989	Modern	Cotton	Cream	36	Wooden S	238.8	83.8	76.2	5	5
90969	Modern	Cotton	Cream	36	Wooden S	238.8	83.8	76.2	4.5	36
89989	Modern	Cotton	Blue	36	Wooden S	238.8	83.8	76.2	4.5	36
87989	Contempo	Cotton	Cream	36	Wooden S	208.3	80	76.2	4.6	55
86987	Chesterfie	Velvet	Grey	36	Wooden S	182.9	72.4	76.2	5	5
86987	Chesterfie	Velvet	Blue	36	Wooden S	182.9	72.4	76.2	5	5
86987	Chesterfie	Velvet	Brown	36	Wooden S	182.9	72.4	76.2	5	5
86987	Chesterfie	Velvet	Purple	36	Wooden S	182.9	72.4	76.2	5	5
86987	Chesterfie	Velvet	Green	36	Wooden S	182.9	72.4	76.2	5	5
85989	Modern	Cotton	Cream	36	Wooden S	279.4	81.3	73.7	5	5
85898	Modern	Velvet	Yellow	36	Wooden S	238.8	83.8	76.2	4.5	36
85898	Modern	Velvet	Green	36	Wooden S	238.8	83.8	76.2	4.5	36
85898	Modern	Velvet	Grey	36	Wooden S	238.8	83.8	76.2	4.5	36
85898	Modern	Velvet	Blue	36	Wooden S	238.8	83.8	76.2	4.5	36
84999	Modern	Cotton	Green	36	Wooden S	238.8	83.8	76.2	4.5	36
83989	Rolled arm	Velvet	Blue	36	Wooden S	193	81.3	83.8	5	15
83989	Rolled arm	Velvet	Grey	36	Wooden S	193	81.3	83.8	5	15
83989	Rolled arm	Velvet	Brown	36	Wooden S	193	81.3	83.8	5	15
80948	Modern	Velvet	Pink	12	Vittoria	88.9	198.1	78.7	4.4	22
79989	Modern	Cotton	Blue	36	Wooden S	309.9	81.3	73.7	4.8	129
79989	Modern	Cotton	Red	36	Wooden S	309.9	81.3	73.7	4.8	129
79989	Modern	Cotton	Beige	36	Wooden S	309.9	81.3	73.7	4.8	129
79989	Modern	Cotton	Grey	36	Wooden S	309.9	81.3	73.7	4.8	129
79989	Modern	Cotton	Beige	36	Wooden S	309.9	81.3	73.7	4.8	129
79989	Modern	Cotton	Red	36	Wooden S	309.9	81.3	73.7	4.5	201
79989	Modern	Cotton	Blue	36	Wooden S	309.9	81.3	73.7	4.5	201
79989	Modern	Cotton	Beige	36	Wooden S	309.9	81.3	73.7	4.5	201

Figure 4.3: CSV data

4.3 Model Building

We built a pipeline in Azure by splitting the data into 0.7 for training and 0.3 for testing. We explored various machine learning models, including linear regression, boosted decision trees,poisson regression and decision trees, to determine the most effective approach for forecasting sofa sales. The selection process involved evaluating each model's accuracy and suitability based on key metrics and predictive capabilities. Among these regressions boosted decision tree yielded the highest accuracy which is best fir for our model.

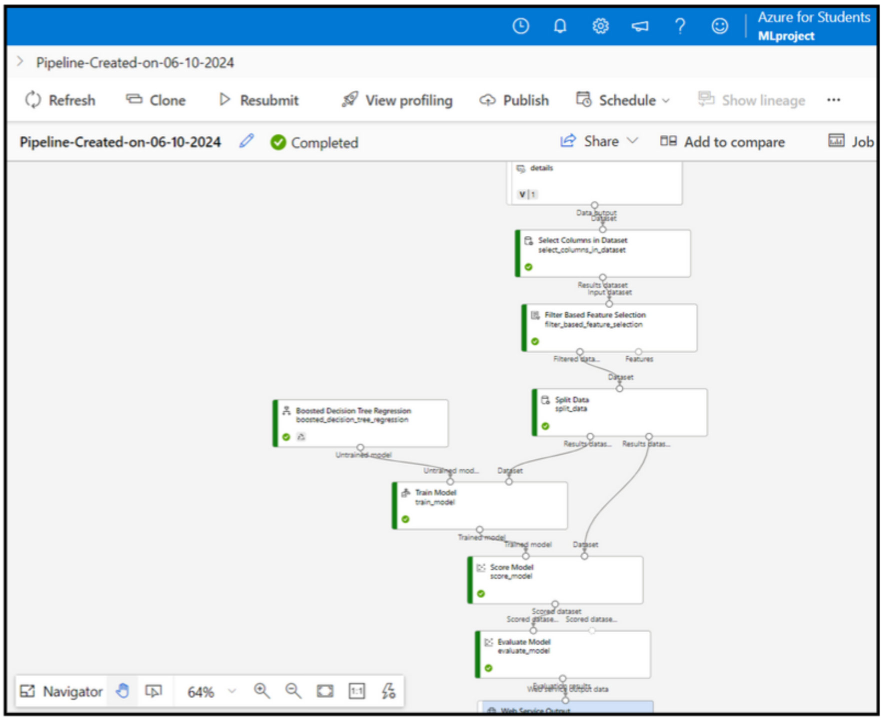

Figure 4.4: Pipeline

4.4 Model Enhancement

To enhance the model's performance, we conducted feature analysis to understand the impact of various factors on sales outcomes. We examined how adjustments in features like price, dimension, rating, and warranty influenced sofa sales. This analysis helped identify key drivers of sales and informed feature selection and engineering, ultimately improving the model's accuracy and predictive power.

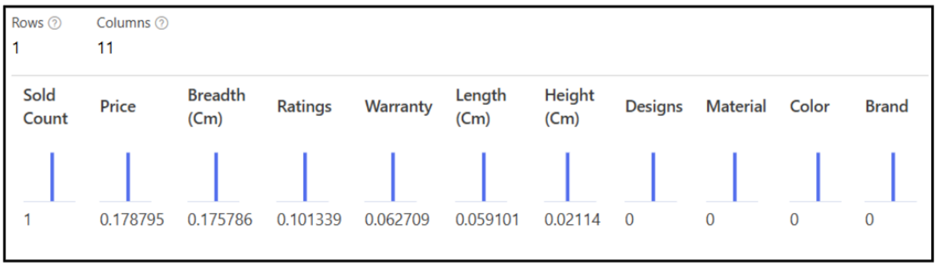

Figure 4.5: Feature Analysis

4.5 Deployment and Validation

The optimized model was deployed on Microsoft Azure, integrating it into a real-time pipeline for continuous sales forecasting. Postman API was used to rigorously test the model's endpoint, ensuring accurate and reliable predictions. The model was set up for real-time operation, with performance closely monitored to address any issues. Additionally, automated alerts and dashboards were deployed to track model accuracy and performance metrics, enabling proactive management and quick adjustments. Ongoing evaluations and feedback, including regular retraining with updated data, were employed to refine the model and enhance its effectiveness in delivering actionable insights. This approach ensured the model remained aligned with changing market conditions and customer preferences.

4.6 Insights and Recommendations

The model's analysis revealed key sales trends and customer preferences. Recommendations include optimizing inventory, adjusting marketing plans, and refining product offerings based on these insights. These actions aim to enhance operational efficiency and align better with market demands.

Chapter 5

Implemention

5.1 Implemention Details

The sales prediction model was deployed on Microsoft Azure, featuring a real-time web interface for smooth access. Continuous data processing was integrated into the system, and performance was validated to ensure accuracy. Optimization techniques were used to enhance the model's efficiency and effectiveness.

5.1.1 System Deployment

- **Real-Time Interface:** Deployed the model on Microsoft Azure, providing a real-time interface with a REST endpoint. This setup allows the model to be accessed and utilized across the web.
- **Cloud Integration:** Integrated the model into Azure's cloud infrastructure for scalable processing. This ensures efficient handling of large volumes of data and high availability.
- **Endpoint Accessibility:** Enabled web access to the model via the REST endpoint, facilitating seamless integration with other systems and applications.

5.1.2 Model Integration

- **System Integration:** The model was incorporated into the existing system architecture. This ensures smooth interaction with data sources and user interfaces.

- **APIs and Services:** Integrated various APIs and services to enhance the model's functionality and accessibility, ensuring that predictions are efficiently delivered.

5.1.3 Performance Testing

- **Postman API Testing:** Tested the model's REST endpoint using Postman API with raw JSON format in the request body. This validated the accuracy and reliability of the model's predictions.
- **Endpoint Verification:** Ensured the endpoint correctly processed data and returned expected results. This step was crucial for confirming functionality of the deployed model.
- **Response Analysis:** Analyzed API responses to verify consistency and correctness. This helped in identifying any discrepancies or issues before full-scale deployment.

5.1.4 Security

- **Risk Assessment:** Evaluated risks such as system downtime, data breaches, and model inaccuracies.
- **Mitigation Strategies:** Used Azure's redundancy and backup features to ensure high availability.Used Azure's built-in security features to safeguard against threats and ensure system integrity.Applied regular validation and updates to maintain accuracy.

5.1.5 Optimization and Tuning

- **Hyperparameter Tuning:** Fine-tuned hyperparameters for both boosted and decision tree regressions. This process aimed to enhance performance of model and prevent overfitting.
- **Cross-Validation:** Employed cross-validation techniques to validate the model's generalizability. This approach helped in ensuring the model's robustness across different datasets.
- **Model Comparison:** Compared performance between boosted and decision tree regressions. This comparison was used to select the best-performing model for the forecasting task.

Chapter 6

Results and Discussions

6.1 Experimental Results

In our testing phase, we utilized Postman to evaluate the model's performance through multiple scenarios. This included sending various types of requests to the model's API endpoint to test its response accuracy and efficiency. We have analyzed how the model handled different input conditions, assessed response times, and checked for consistency in the results. Additionally, Postman was used to validate edge cases and ensure the model's reliability under different scenarios. This thorough testing process helped identify potential issues and confirm the model's readiness for deployment.

6.1.1 Performance Metrics

The performance metrics for our sales prediction model highlight the impact of the boosted decision tree approach. This model achieved the highest accuracy of 0.96, demonstrating its strong predictive capabilities. Additionally, it recorded a lower mean absolute error, indicating precise predictions with minimal deviations from actual values. These metrics confirm that the boosted decision tree model is highly reliable for forecasting sales. Furthermore, the model exhibited robust performance across various test datasets, showcasing its versatility and generalization ability. The reduced overfitting and consistent results across different scenarios underscore the model's robustness in handling diverse data patterns.

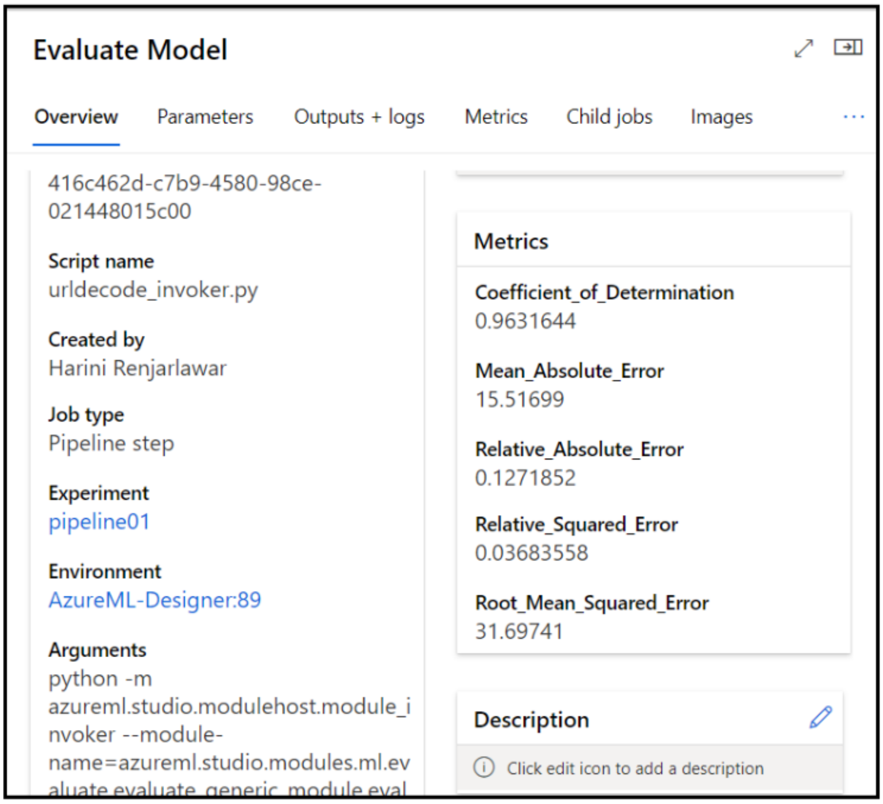

Figure 6.1: Evaluation Of Regression Model

6.1.2 Warranty Ratings

We compared two products of the same cost but with different warranties and ratings. The first product had an 18-month warranty and a rating of 4.2, while the second had a 36-month warranty and a rating of 4.8. The model predicted a higher sold count for the product with the longer warranty and higher rating. This result indicates that customers prioritize quality and reliability over initial cost. This insight was further validated through customer feedback analysis, which highlighted a preference for longer warranties and higher-rated products. The findings underscore the importance of investing in quality improvements and warranty extensions to enhance customer appeal and drive sales growth.

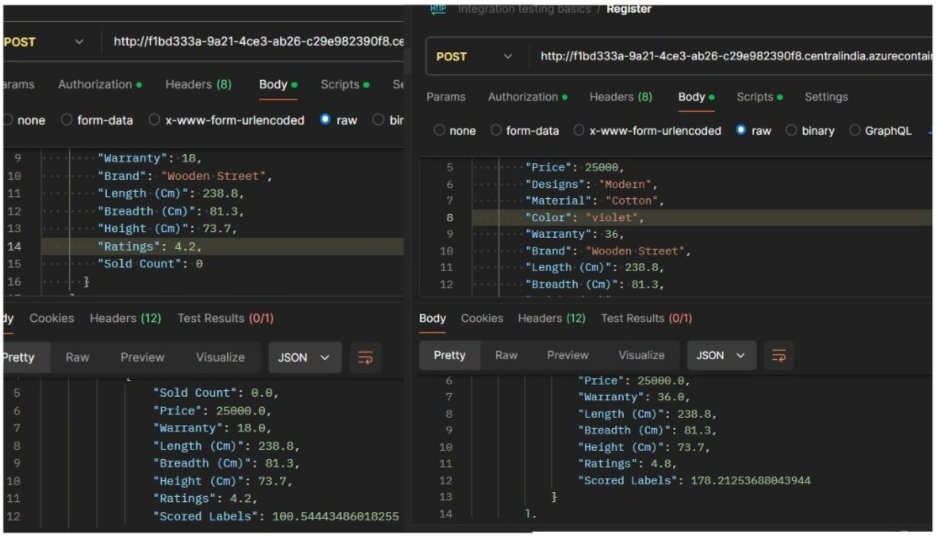

Figure 6.2: postman work

6.1.3 Value-for-Money

We tested two products with high-quality inputs; one was priced at an average cost, and the other at a higher cost. The model showed a higher sold count for the average-cost product, suggesting that customers value value-for-money and prefer high-quality inputs at reasonable prices. This finding highlights that while customers prioritize product quality, they are also highly sensitive to price, particularly when the perceived benefits of a higher-priced product do not notably exceed those of a more affordable option.

This insight into consumer behavior can significantly influence pricing strategies. By offering high-quality products at competitive prices, businesses can better align with customer preferences, thereby improving market competitiveness and driving higher sales volumes. Additionally, this approach can enhance overall customer satisfaction, as consumers are more likely to perceive they are getting excellent value for their money. Strategically balancing quality and cost will be essential in capturing and retaining a broader customer base while optimizing profitability.

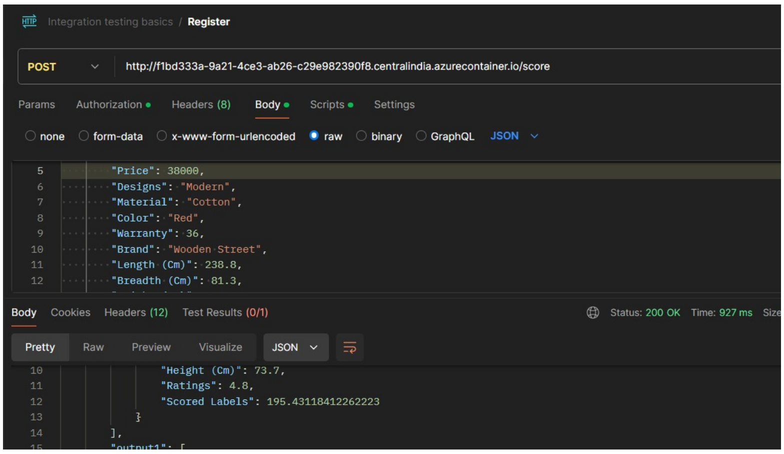

Figure 6.3: Sales-Prediction Response

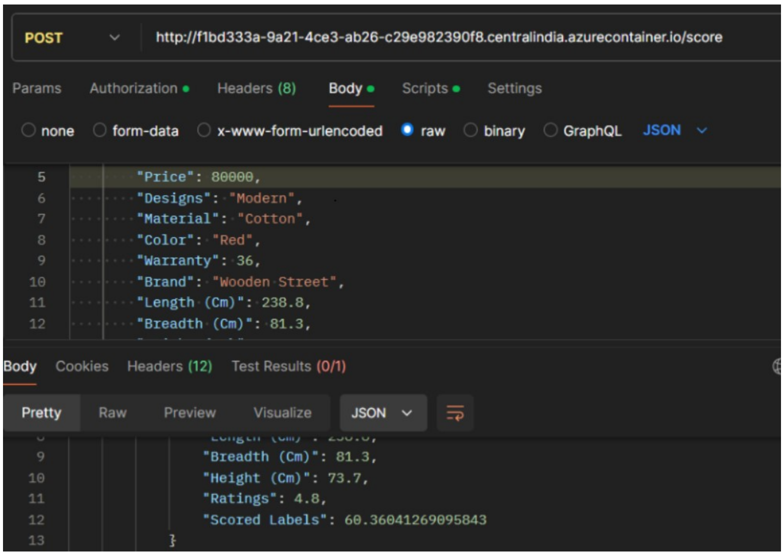

Figure 6.4: Sales-Prediction Response

6.2 Discussion

These results confirm that our model effectively captures customer preferences for quality, reliability, and value-for-money, offering insights that can enhance customer satisfaction,optimize pricing strategies and boost sales performance.The model's insights provide actionable strategies for improving market positioning and meeting customer expectations.

6.2.1 Improvement and Recommendations

To enhance the sales prediction model further, several Enhancements and Suggestions can be considered. Firstly, refining feature engineering by incorporating additional factors such as seasonal trends, regional preferences, and promotional events can provide a more nuanced understanding of sales drivers. Additionally, employing model ensemble techniques, such as stacking or blending, can leverage the strengths of multiple models to boost predictive accuracy and robustness.

- **Enhance Data Quality:** Address gaps and inconsistencies; incorporate additional data sources.
- **Tune Model:** Adjust hyperparameters and explore different algorithms for better performance.
- **Use Cross-Validation:** Implement robust cross-validation to ensure model generalization.
- **Gather User Feedback:** Collect and incorporate feedback to refine the model and improve its effectiveness.
- **Optimize Feature Engineering:** Refine feature selection and engineering to better capture relevant patterns and relationships in the data.
- **Integrate Real-Time Data:** Incorporate real-time data feeds to keep the model updated with the latest market trends and customer behavior.

Chapter 7

Conclusion

The sales prediction model effectively forecasts sofa sales using historical data and seasonal trends. Data from Wooden Street, processed with Microsoft Azure, led to the development of a highly accurate boosted decision tree regression model with a 0.96 accuracy rate. This model provides valuable insights for optimizing sales strategies, benefiting customers, manufacturers, and supply chain managers by accurately predicting sales based on factors like dimensions, ratings, warranties and price.By highlighting the importance of quality and warranties, model supports efficient resource allocation, production planning, and inventory management. It aids decision-making by emphasizing value-for-money and helps reduce waste through precise sales predictions.

Future work can expand the model by incorporating additional data sources such as customer reviews and market trends to improve predictive accuracy.Exploring advanced machine learning techniques and integrating real-time data could enhance the model's adaptability and responsiveness to market changes. Additionally, developing a user-friendly interface for stakeholders to interact with the predictions and recommendations can further streamline decision-making processes and drive more targeted sales informed strategies.

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