HUMBER INSTITUTE OF TECHNOLOGY

AND ADVANCED LEARNING

(HUMBER COLLEGE)

OptiOrder: Predictive Analytics for Order Prioritization

Assignment 1

Machine Learning 2 - BIA-5402-0LB

Group - 5

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Introduction:

In the fast-paced world of modern business, where competition is fierce and customer expectations are higher than ever, the ability to efficiently manage and prioritize orders is paramount. In this report, we delve into the realm of predictive analytics to tackle the challenge of order prioritization. By harnessing the power of machine learning, we aim to develop a model that can accurately predict the priority of orders based on a variety of factors. By doing so, businesses can streamline their operations, allocate resources more effectively, and ultimately enhance customer satisfaction.

Data Overview:

Our dataset comprises a comprehensive collection of order data, encompassing 1500 entries and 8 distinct features. These features include essential information such as Order_ID and Product_ID, as well as key variables like Order_Quantity, Priority, Product_Type, Location, Weight, and Size. Each entry in the dataset represents a unique order, providing a rich source of information for training and testing our predictive model. The inclusion of diverse features allows us to capture the multifaceted nature of order prioritization, taking into account factors ranging from product characteristics to logistical considerations.

Table Structure:-

- **Order_ID**: This is a unique identifier for each order. It helps in tracking and referencing specific orders in the system.
- **Product_ID**: This is a unique identifier for each product. It is used to identify the specific product that has been ordered.
- **Order_Quantity**: This represents the number of units of the product that have been ordered. It indicates the quantity of the product that needs to be fulfilled.
- **Priority**: This field indicates the urgency or importance of the order. Orders can be prioritized based on various factors such as customer requirements or delivery deadlines.
- **Product_Type**: This categorizes the product into a specific type or category. It helps in identifying and grouping similar products.
- **Location**: This specifies the location where the product needs to be delivered or the location of the inventory. It is essential for logistics and delivery planning.
- **Weight**: This indicates the weight of the product. It is important for shipping calculations and handling requirements.
- **Size**: This specifies the dimensions or size of the product. Similar to weight, it is crucial for packaging, shipping, and storage considerations

Literature Review:

Order prioritization is a critical aspect of operations management in various industries, including e-commerce, retail, and logistics. Traditional methods of prioritization often rely on predefined rules or manual intervention, which can be time-consuming and prone to errors. In recent years, machine learning techniques have emerged as a powerful tool for automating and optimizing order prioritization processes. Neural networks, in particular, have garnered significant attention due to their ability to learn complex patterns from data and make accurate predictions. By reviewing existing literature on the topic, we gain valuable insights into the potential applications of machine learning in order prioritization and identify best practices for model development and evaluation.

Data Analysis:

Before training our predictive model, we perform a series of preprocessing steps to prepare the data for analysis. This includes encoding categorical variables using Label Encoder to convert textual data into numerical format, which is required for training machine learning models. Additionally, we split the dataset into training and testing sets to assess the performance of our model on unseen data. To ensure that our model can effectively learn from the data, we apply standard scaling to normalize the feature values, preventing any single feature from dominating the learning process due to differences in scale.

Distribution of Order Quantity

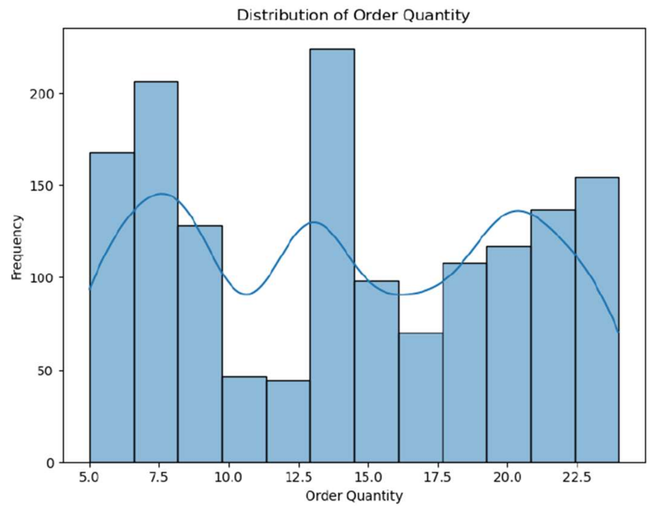

Fig :- 1

The chart indicates that order quantities tend to cluster around certain values (approximately 7.5, 12.5, and 15), with fewer orders around the quantity of 10. The presence of multiple peaks and troughs suggests that the order quantities are not uniformly distributed but have specific preferred values. The KDE line provides a smooth representation of this distribution, highlighting the same patterns seen in the histogram.

Distribution of Weight

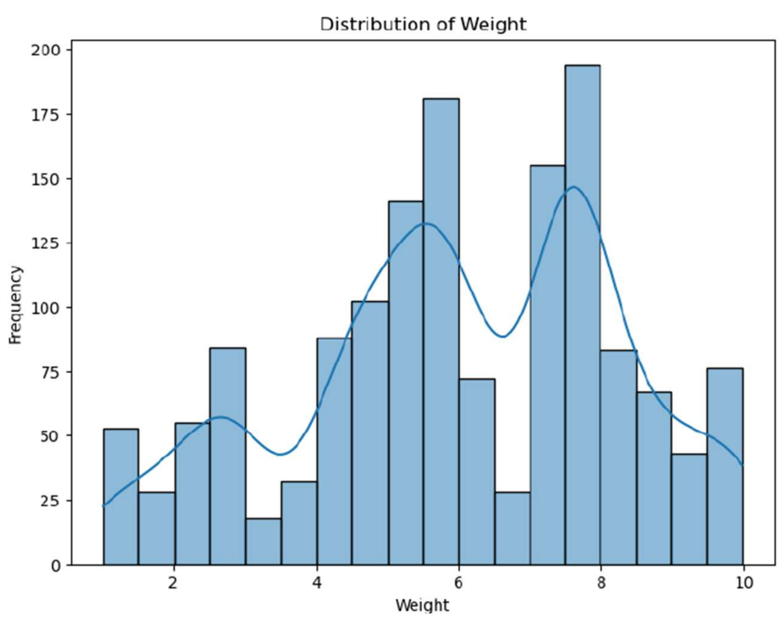

Fig:- 2

It helps to understand the distribution of a single numerical variable ('Weight').
It provides insight into the frequency of different weight values in the dataset, revealing the central tendency, spread, and shape of the distribution. The KDE curve adds a smoothed view of this distribution.

Scatter Plot 'Order Quantity' vs 'Weight'

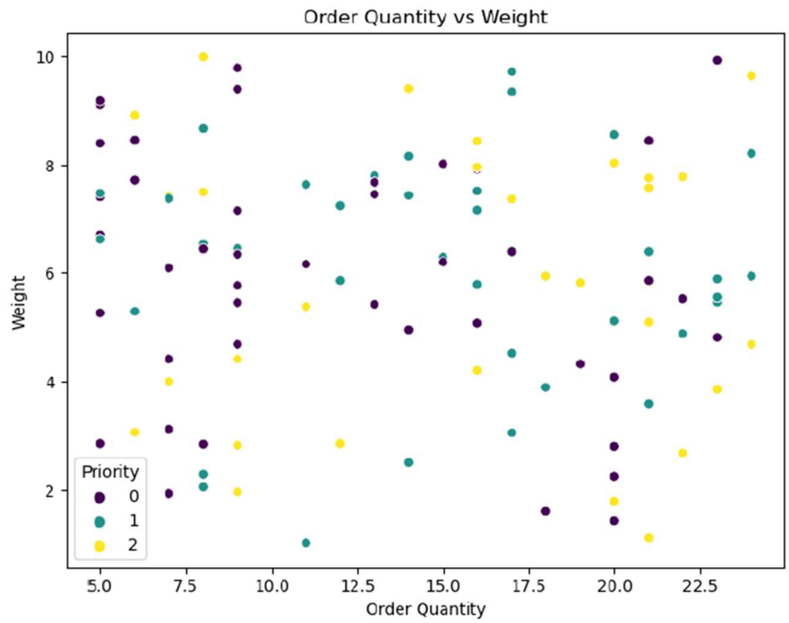

Fig: 3

It helps to understand the relationship between two numerical variables.('Order Quantity' vs 'Weight') It helps identify patterns, trends, and potential correlations between order quantity and weight. The use of color (hue) adds another layer by showing how 'Priority' affects this relationship.

Model Training and Evaluation:

For our predictive model, we employ a Multi-Layer Perceptron (MLP) classifier, a type of artificial neural network that consists of multiple layers of interconnected neurons. By specifying the architecture of the neural network, including the number of hidden layers and neurons, we can tailor the model to the specific characteristics of our dataset. After training the model on the training data, we evaluate its performance using the testing data and generate a classification report to assess its accuracy, precision, recall, and F1-score for each class. This provides valuable insights into the strengths and weaknesses of our model, allowing us to identify areas for improvement and refinement.

We trained an MLP classifier with two hidden layers containing 10 and 5 neurons, respectively, using the training data. The model was evaluated using the testing data, and the following classification report was generated:

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.95	0.79	0.86	199
1	0.79	0.57	0.66	115
2	0.65	0.96	0.77	136
Accuracy			0.78	450
Macro Avg	0.8	0.77	0.76	450
Weighted Avg	0.82	0.78	0.78	450

Table:- 1

- Precision: This is the ratio of true positive predictions to the total predicted positives. It indicates the accuracy of the positive predictions made by the model.

- Accuracy: The ratio of correctly predicted instances to the total instances. The overall accuracy of the model is 0.78, indicating that 78% of the predictions were correct.

- Macro Average: The macro average is the arithmetic mean of precision, recall, and F1-score across all classes, giving equal weight to each class.

- Weighted Average: The weighted average considers the support (the number of true instances) of each class when calculating the average. It provides a more balanced performance metric if the class distribution is imbalanced.

Summary:

Class 0 has high precision and reasonable recall, resulting in a high F1-score.

Class 1 has moderate precision and lower recall, leading to a lower F1-score.

Class 2 has lower precision but very high recall, with a reasonably high F1-score.

The overall model accuracy is 78%.

The macro average and weighted average provide insights into the model's performance across all classes, with the weighted average accounting for class distribution.

Model Performance:

Upon evaluating the performance of our model, we observe promising results, with an overall accuracy of 78.44%. However, a closer examination of the classification report reveals discrepancies in the precision and recall scores across different priority levels. While the model excels in classifying Low priority orders, it struggles to achieve comparable levels of precision and recall for Medium priority orders. This suggests that further optimization of the model may be necessary to enhance its performance, particularly for orders with medium priority levels. By fine-tuning the model parameters and exploring alternative architectures, we can potentially improve its predictive capabilities and achieve higher levels of accuracy across all priority levels.

Comparison and Business Implications:

To contextualize the performance of our model, we compare it with existing rule-based systems or manual prioritization methods commonly employed in business operations. By conducting a side-by-side comparison, we can assess the effectiveness of our machine learning approach in streamlining order processing operations and improving overall efficiency. Furthermore, we explore the potential business implications of our predictive model, highlighting its role in optimizing resource allocation, inventory management, and delivery scheduling. By accurately predicting order priorities, businesses can minimize delays, reduce costs, and enhance customer satisfaction, ultimately gaining a competitive edge in the marketplace.

Conclusion:

In conclusion, our foray into predictive analytics has yielded promising results in the realm of order prioritization. Through the development of a machine learning model capable of accurately predicting order priorities based on diverse features, we have demonstrated the potential for automation and optimization in order processing operations. While further refinement and evaluation may be necessary to achieve optimal performance, our approach lays the groundwork for future advancements in this field. By embracing the power of machine learning, businesses can unlock new opportunities for innovation and efficiency, driving growth and success in the digital age.

References:

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