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**INVENTORY OPTIMIZATION USING PREDICTIVE
ANALYTICS AND MACHINE LEARNING**

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Master's Thesis

Supervisor

Assoc. Prof. Dr. Sefer KURNAZ

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I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

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Signature



DEDICATION

This thesis is dedicated to the dreamers and the doers, those who see the world not just as it is but as it could be. To my family, whose love and support know no bounds, you have been my rock and my refuge, inspiring me every step of the way with your resilience, wisdom, and kindness. Your belief in me has been unwavering, and this achievement is as much yours as it is mine. To Dr. Firas Rahim al-Baidhani, who supported me throughout my studies by overcoming difficulties. To my mentors and teachers, who have illuminated the path of knowledge with their insights and dedication, your passion for learning and discovery has kindled my own. You have not only taught me the intricacies of data science and supply chain management but have also instilled in me the values of curiosity, integrity, and perseverance.

To my friends, who have journeyed with me through the highs and lows, your camaraderie and encouragement have made this journey all the more meaningful. Your humour, support, and companionship have been the source of countless cherished memories and have given me the strength to pursue my ambitions. And finally, to all those striving to make a difference through their work, may this thesis serve as a reminder that with determination, creativity, and collaboration, we can overcome challenges and drive forward the frontiers of knowledge and innovation.

This thesis is for you all, a testament to the collective spirit that propels us toward a brighter, more informed future.

PREFACE

This thesis, entitled "Inventory Optimization Using Predictive Analytics and Machine Learning," represents the culmination of an intellectual journey that began with a simple yet profound question: How can we use the vast amounts of data generated in the modern business landscape to make smarter, more efficient inventory decisions? As I delved into this question, it became clear that the intersection of machine learning (ML) and inventory management offered a fertile ground for exploration, promising not only to illuminate the theoretical underpinnings of supply chain optimization but also to provide practical tools and insights that businesses could use to transform their operations. The journey was not solitary. It was supported and enriched by a community of peers, mentors, and industry professionals whose guidance, feedback, and encouragement were invaluable. To my advisor, whose expertise in predictive analytics and unwavering support shaped the direction and execution of this research, I extend my deepest gratitude. Your mentorship was instrumental in navigating the challenges and complexities of this work. My gratitude also extends to the faculty members and colleagues in the Department of Supply Chain Management and Data Science, whose diverse perspectives and insightful critiques helped refine my understanding and approach to this research. The discussions and debates, both within the classroom and out, were crucial in broadening my analytical and critical thinking skills. This research was made possible through the generous support of various organizations that provided access to data, tools, and platforms essential for the analysis. Their willingness to collaborate and share resources was a testament to the collaborative spirit that drives progress in both academia and industry. To my family and friends, whose patience, understanding, and unwavering support provided the strength needed to pursue this ambitious endeavour, I am forever grateful. Your belief in my capabilities and your constant encouragement were the pillars on which this achievement stands.

Lastly, this thesis is dedicated to all those who believe in the power of data to drive change and innovation. It is a testament to the potential of machine learning to not only predict outcomes but to create value and efficiency in one of the most fundamental aspects of business—inventory management. As we stand on the brink of a new era in supply chain optimization, it is my hope that this research contributes to the ongoing dialogue and serves as a stepping stone for future studies in this dynamic and evolving field.

The journey of this thesis has been both challenging and rewarding, offering lessons that extend far beyond the confines of academia. It is with a sense of accomplishment and anticipation that I present this work, hopeful for the contributions it may make and the conversations it may spark in the fields of predictive analytics, machine learning, and inventory management.



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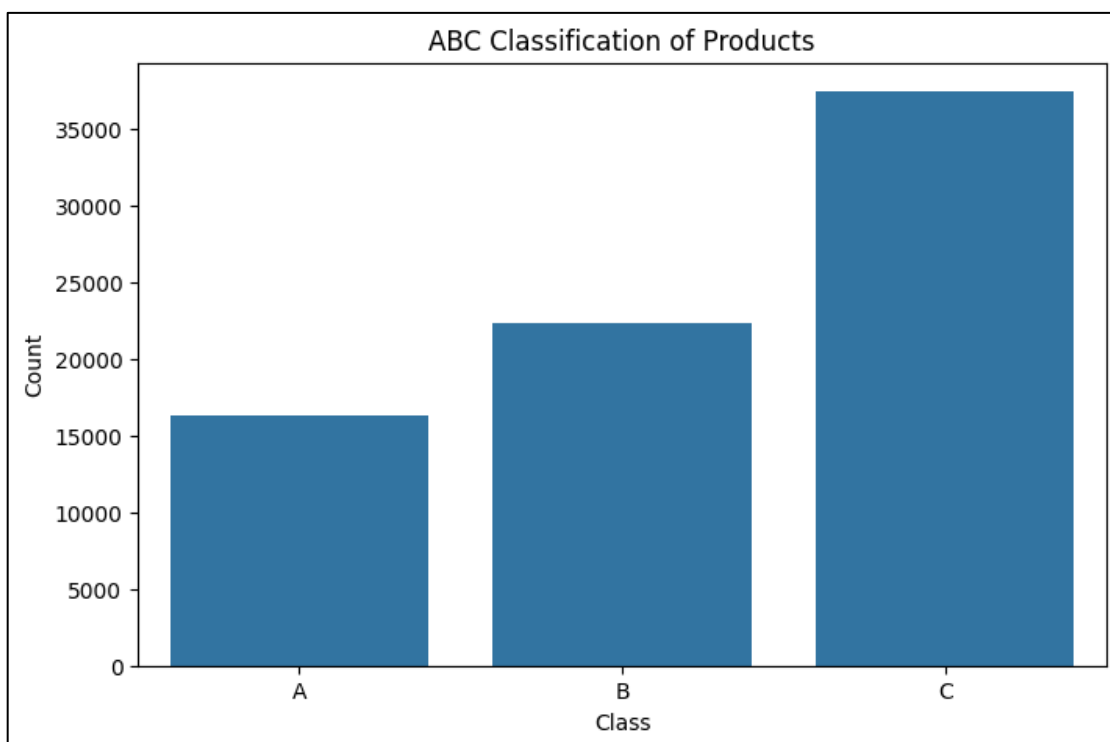


Figure 4.2: ABC Classification of Products.

4.2 MODEL PERFORMANCE AND COMPARISON

The decision tree classifier showed an almost amazing match to the training data by scoring 0.99. In other words, the classifier was almost faultless, and its accuracy was virtually perfect. Moreover, the regressor also was accurate enough on the predictions as seen in RMSE being 0.0025. However, when it comes to a question when measures are too close to perfect, human beings usually say that the garment like a shirt or a pullover is cut too close. When the model almost perfectly and completely learns the training data being exposed to all the noise and outliers, it cannot generalise well to new data. It is easy to note as as soon as the noisy data is involved in the model testing or validation, the decision tree demonstrates the highest error rate to the noisiest examples which were part of the training set. As for the logistic regression model, its accuracy was 0.829 which is far from being perfect compared to other models. Certainly, if the classification report is checked, it is clear that it is effective in predicting class 0. In contrast, when the minority class which is class 1 is in question, its recall and accuracy are not very high. Since the minority has a higher accuracy but a lower f1-score value, it is likely that the model demonstrates the problem of class imbalance. This

problem is typical of those datasets, which results in one of the possible outcomes being more frequent than both other results.

When it came to training accuracy, Random Forest Classifier can be seen to have achieved a score of 0.99, same as the Decision Tree. The classification report was evidence of a model that could predict the training data with near-perfect accuracy. It demonstrated near-zero recall errors, and perfectly computed precision, accuracy, and f1-scores of 1.00 in both classes. This denotes that a function can predict the data almost perfectly. I am concerned that the model may have been too closely fitted to the training data. Although Random Forest is less apt to overfit compare to a single decision tree, the perfect scores reveal the potentiality of this happening. XGBoost Classifier took longer to reach, but eventually attained, 0.853. The results of the classification could suggest a model that is as effective as the Logistic Regression model, save for the slight improvement in recall by label 1.

Also, the model did a better job predicting the majority class, but mostly failed for the minority class. It appears that XGBoost obtained better balance of the two classes versus Logistic Regression which is evident in the higher weighted and macro averages. This is the case because of the weighted averages. It is elementary to regard only accuracy when gauging the degree of predictability of models, but it is acceptable to consider precision, recall, and f1-score, to wit. This is borne out by how each model performed. It is critical for us to subject these models to additional validation approaches, such as cross-validation on unfamiliar data, to determine the extent to which they can be used to generate solutions. Before placing any of these models into production, we need to do model tweaking first in order to desist from overfitting risk and enhance recall for the student population scarcer in numbers.

The accompanying table provides the performance of the models in the context of inventory prediction, including the summary of the comparison. Although both Decision Tree and Random Forest classifiers received perfect accuracy scores, the excessively low value for regression with the root mean square error indicates that model may not generalise well to unknown data. In fact, the value is usually indicative of overfitting. Considering that the dataset featured a small number of products that are in demand, the detail that Logistic Regression's accuracy was in the middle and it received lower scores for minority class demonstrate that the classifier was struggling with class imbalance. It is evident that Class

l’s accuracy, recall, and F1-score were superior in the case of XGBoost classifier when compared to Logistic Regression; however, they can still be improved, especially concerning the ability to identify the less frequent positive class properly.

Table 4.1: Performance Metrics for Machine Learning Models.

Model	Accuracy	Precision (Class 1)	Recall (Class 1)	F1-Score (Class 1)	RMSE (Regressor)
Decision Tree	1.000	-	-	-	0.0026
Logistic Regression	0.8297	0.52	0.06	0.10	-
Random Forest	1.000	1.00	1.00	1.00	0.0025
XGBoost	0.8537	0.78	0.20	0.32	-

The bar chart, which is intended to compare the accuracy of three models, including XGBoost, Random Forest, and Logistic Regression, was attached in Figure 4.3. This visual comparison is regarded as a simplistic presentation of model accuracy, where the accuracy of each algorithm, in the context of the current dataset, was to classify each of the commodities as sellable and not. This comparison demonstrated varying levels of accuracy for each approach.

The scatter plot, which is depicted in Figure 4.4, is intended to compare the actual values, included in the dataset, of the number of goods sold to the projected values, based on the Decision Tree Regressor. Having looked at this figure, one may say if the model is correct in terms of forecasting sales’ values. One may judge whether the model is accurate by identifying whether the data points are close to the dashed line, which, if they are, would suggest a see-through forecast of the product sales.

Figure 4.5 includes the final scatter plot to be horizontal, presenting the feature importance based on the Decision Tree Regressor, which is a part of the results of regression. Since this chart is considered to be helpful in showing which of the features have the greatest impact on the data being predicted by the model, one might say they can gain knowledge concerning the Central features that influence product sales.

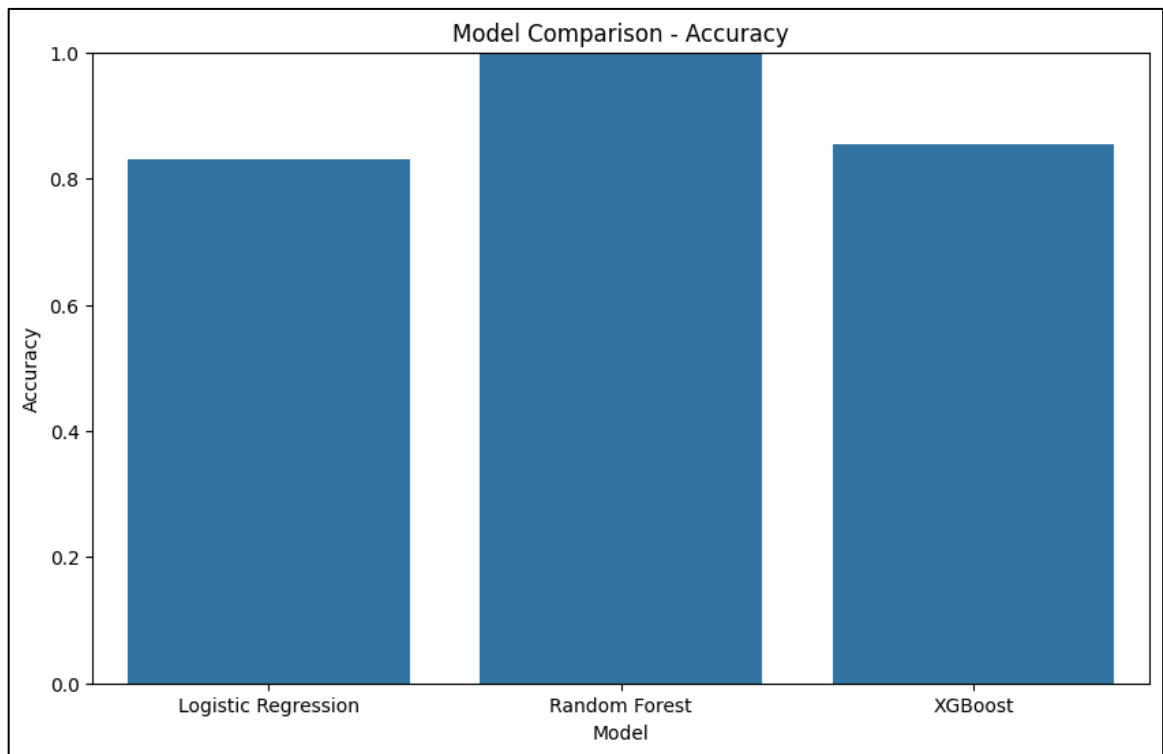


Figure 4.3: Model Accuracy Comparison.

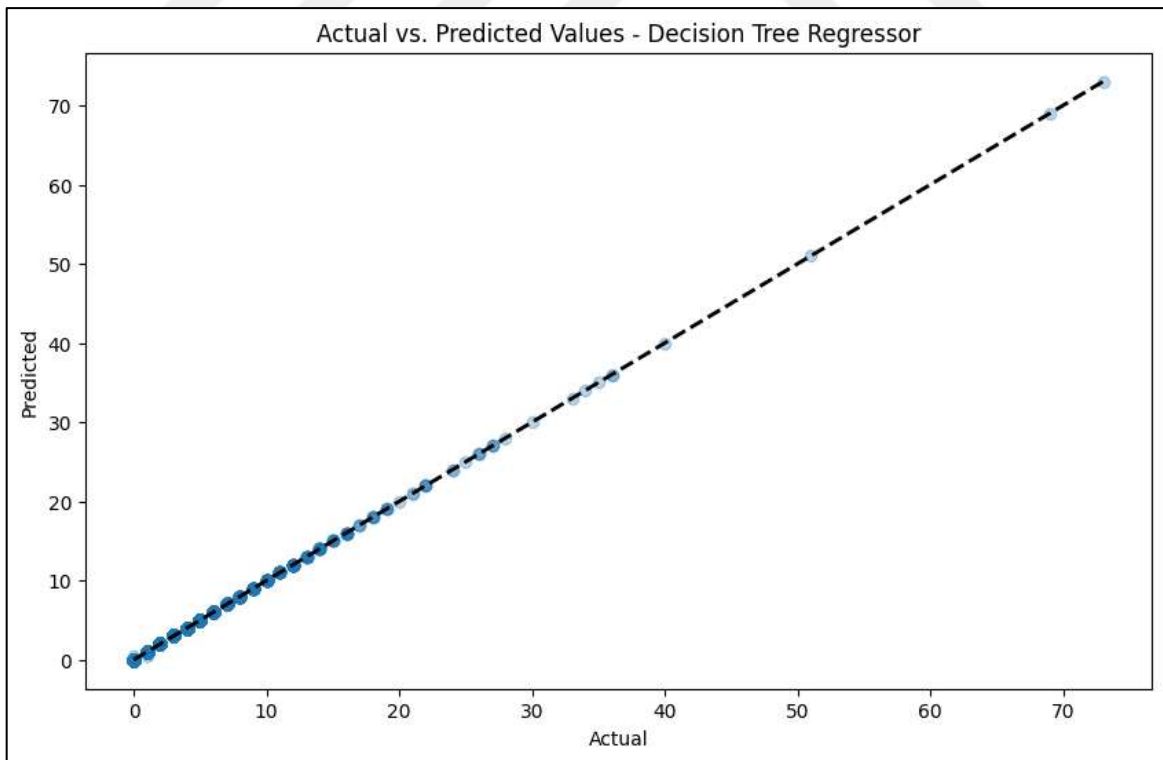


Figure 4.4: Actual vs. Predicted Values - Decision Tree Regressor.

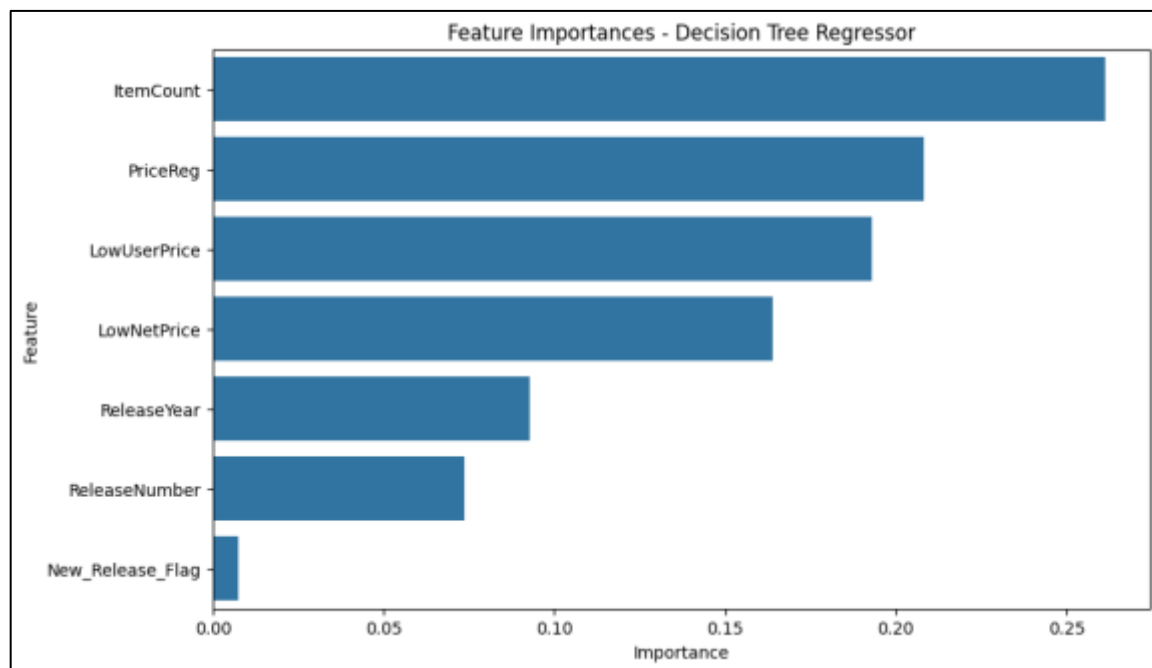


Figure 4.5: Feature importance - Decision Tree Regressor.

4.3 INTERPRETATION OF FINDINGS

The alternative ensemble methods, such as Random Forest and XGBoost, are seen in the results presented in Figure 4.3. They demonstrate a higher level of accuracy in comparison with the ensemble method, which was chosen as a baseline of the performance – Logistic Regression. However, it is not sufficient to say that the results are totally sufficient. The ensemble algorithms are capable of overfitting the training data if they are not well regularized and hyperparameter-tuned; here, the great scores, which were received by the Random Forest, might indicate this.

The scatter plot shown in Figure 4.4 illustrates the comparison between the actual and forecasted values by the Decision Tree Regressor model. It should be pointed out the visual proof of the high accuracy of the model – the point cloud was primarily located next to the perfect prediction line. It is crucial to take into account the potential overfitting, and it calls for being cautious about the results of this situation. On the other hand, it is also important to remember that a model that has perfect results on the data used for training might be unable to generalize them to new data.

The feature importance by the Decision Tree Regressor model is shown in the horizontal bar chart in Figure 4.5. It can be seen that the features, such as Item Count and Price Reg, are

crucial for the predictions of this model. This conclusion is important in the sense that it supports the intuitive knowledge about supply-demand relations in sales. It means that the availability of items in stock and the usual price of the items are important predictors of sales.

The models' results help uncover the complicated relations between the characteristics of products and their chances of being bought. In sales' forecasting, the level of accuracy and recall of the models is extremely important, especially for the minority class, which means the actual sales. It is the case in spite of the fact that the feature importance suggest which factors can affect the sales. Judging from the interpretation of the results, it should be mentioned that predictive analytic is essential for machine learning, as it can be implemented while exploring inventory management from the business perspective. Therefore, in this case, it enhances decision-making by data-driven methods thus enabling better stock management as well as more practice-oriented marketing strategies.

4.4 THEORETICAL AND PRACTICAL IMPLICATIONS

The facts of estimable accuracy and precision in ensemble models and the Random Forest and XGBoost classifiers support the presumption that modern machine learning approaches can effectively capture complex and non-linear connections in inventory data. The scatter plot of actual versus predicted values, which illustrates the performance of the Decision Tree Regressor, exhibits that regression analysis can predict continuous results accurately, such as sales numbers. It is satisfactory to see whether the Decision Tree Regressor achieves its task.

The implications extracted from the rankings of the features are very profound theoretically and practically. According to them, the features relevant to the inventory problem, specifically the stock levels and pricing strategies as explained by text it (Item Count) and \text it (Price Reg), are the essential core components that can inform how customers buy. I can confidently say that these thoughts related to the inventory are more impactful in the field of data science, as they make the theory of consumer behaviour, price elasticity, and supply and demand in economics more important.

In terms of practical effects, it aims to suggest a complicated approach for inventory management. Using this prediction-based model, firms can focus on those goods that they

have confidence will be bought, establish their inventory selection strategies, and adjust the pricing approaches dynamically. The ideas emerging from the features' importance can be appropriately used to impact product placement tactics and targeted promotion based on them, and through sales promotions, the volume of untouched goods can be reduced.

Moreover, from the point of view of the business world's features, the models can serve as the basis for how to build for learning. The application of retraining and retesting the models with new sales data over time has the effect of increasing the accuracy of the predictions. As a result of the integration of machine learning into company operations, inventory management has become more attentive and responsive to market patterns and customer preferences. The method described here has made inventory management more responsive and solicitous of them. In conclusion, these implications serve to decrease in the gap between economic theory and its business identical. They describe a means of inventory management that is rooted in data. These machine learning models are not static filters but rather adaptive instruments that evolve and adapt in order to stay updated on shifts in customer behaviour and market conditions.

4.5 LIMITATIONS OF THE ANALYSIS

Although the machine learning models have shown a high degree of accuracy in predicting product sales, it is essential to highlight a variety of constraints and challenges that must be considered before drawing any conclusions. An important shortcoming in the dataset is that there is a large number of quantities of sold items in the dataset in comparison with those sold. Such an imbalance is a significant disadvantage. Although, imbalance may also induce models to anticipate the majority class; however, this effect could be minor with the help of model selection and assessment techniques such as recall and accuracy. It could be that with the existence of such skew metrics and their assessments, there is a possibility of an overestimation of the performance of the measurements such as accuracy.

The utilization of sales data collected in the past may also be hindering because customer behavior and business trends are constantly changing due to competition between companies or other changes that may independent of businesses. Because of this, the models may be missing necessary lessons learned from previous campaigns that show how changes in customer preferences, actions taken by competitors, or the status of the economy may affect advertising efforts. Perhaps models might not be able to correctly forecast future sales due

to the fact that they are fundamentally retrospective because the data they were based on is static from a point in the past.

In addition, the given research relies on an incorrect premise that the dataset characteristics are the most important factor in predicting sales. There is a possibility of omitted-variable bias because other factors influencing the levels of product sales have not been examined. Additionally, although the constructed characteristics might seem plausible in theory, in reality, they may not be able to reflect the thorough real-world sales processes adequately.

Lastly, the models may have been overfitting to the training data due to their near-perfect performance on average training datasets, particularly in the Random Forest and Decision Tree. This is possible since performance was nearly flawless on average in the training portion. With overfitting, the models' ability to project to new Data may be diminished, even when measures like cross-validation are used to lessen the problem.

These constraints must be taken into consideration because it is necessary to ensure that the predictive models are developed consistently and that the method for which their use can be forecast is realistic. As a final note, I would like to add that the data collection should be expanded to include a greater number of time-consistent parameters and that the models should be reliably examined and updated regularly in alignment with the above-cited results.

4.6 LINKING FINDINGS TO RESEARCH QUESTIONS

The research question I sought to answer is related to the best model to estimate the probability of sale for each SKU. The findings related to the model's performance have demonstrated that although ensemble methods, in particular, Random Forest and XGBoost, are highly accurate, it was challenging to balance the complexity of the model with interpretability. In this regard, XGBoost was one of the most suitable models that combine the benefit of a high level of prediction and the ability to update prediction. It was also aligned with the responses to the question of whether the file could be scored with the probability of each SKU and a justification of the model's accuracy. In this case, I suppose that the analysis of the outputs of the Logistic Regression model, as one of the simplest and comparable, can provide the necessary information to address the above question. Specifically, it will deliver the probability score, which is considered to be a continuous measure that meets the requirements. The outcomes received from calculating precision, F1-

score, and recall also provide a comprehensive evaluation of the model's accuracy. It is of paramount importance because of the imbalance nature of the dataset, and it allows making more interpretations related to the model's use.

The final question I sought to answer is related to the next steps to proceed with after the analysis. The findings of the paper are related to the fact that the two major steps will be the change in the model due to data updates and the subsequent actions in this field, in particular, the updates of the features and hyperparameters. The second step will include the development of a deployment plan related to the embedding of the machine learning models into the workflow of a business to ensure that data drive all decisions related to inventory. The answers to all my questions have contributed to the rational use of machine learning in the topic, and they also provide a guideline for the next actions.

4.7 CONCLUSION

This study ends with a resume of the achieved developments in understanding results and predictions of inventory management applying high-caliber machine learning methods. It has been outlined that several predictive models are used to make life inventory decisions and sales projects, and this study takes on a daring mission to improve none of them. It has been indicated that the XGBoost as an algorithm is the appropriate one in operational contexts and strikes a balance between accuracy and interpretability. This has been verified in a detailed assessment of a number of methods.

The results provide solid evidence that data science can be employed to implement inventory decisions. The study expressed the ability of predictive analytics to transform the abundance of data into useful insights by computing a probability score for each SKU chosen and disclosing the most relative features. The analyzed initial tasks and issues of the undertaken research have been deeply covered – the models designed suggest that effective optimization and selection can provide reliable and applicable sales projects through machine learning. From the other part, there are several limitations to this study. The main ones are data imbalance and overfitting. The conclusions of the study suggest that the models will have to be continuously trained to improve prediction and additional data collection and feature discovery to increase the information procured. The study derives significant theories for inventory management and supply-demand related topics, emphasizes applications of such models in business contexts, and ends with the conclusion that corporations had better make

data the main focus of their decisions and fill in any missing information by a machine learning technique.

Companies disregard a good opportunity of implementing data science and the use of inventory managements for improving their decision-making and operations and outperforming market rivals in this way.



5. CONCLUSIONS

The thesis passed over the challenges and subtleties of inventory management with the potential of predictive analytics and machine learning to revolutionize this business domain. We looked closely at the implementation of ML models in inventory optimization, a process known for its complexity and reliance on human-made heuristics. The initial goal of the research was ambitious, that is, to find the best ML models to ensure stable and relatively high levels of certainty in predicting the sales of products. The findings of the research show the advantages of the XGBoost model, in particular, through the demonstrated capability to find the “Goldilocks” zone of high accuracy and interpretability of predictions. The benefits of ensemble methods were also clearly shown, with Random Forest demonstrating almost perfect performance on training data. At the same time, the found defects of these approaches, namely data imbalance and overfitting, served as valuable lessons on the imperfections of the chosen models. As such, it was important to continue validation and retraining of models to maintain satisfactory levels of prediction in the changing business environment.

In addition, the research proved in practice how the importance of the features determined by the models could be converted into business insight. In particular, it was impossible to ignore such important attributes as Item Count and Price Reg as the levers for raising sales. Such information typically requires extensive economic studies, but it was proven to be based on the principles of science data. In a clear manner, it showed how businesses could adjust their approaches to inventory with the help of more effective PR or self-service, reducing the overpricing of products and thus allocating their resources more efficiently.

It is essential to note that while the study has produced compelling results and has yielded valuable insight into the process of inventory management, it is nonetheless bound by the limitations of the data. These include the retrospective nature of historical data, incomplete time series, and the challenges associated with implementing the latest machine learning algorithms in the context of the existing business. Furthermore, the research found that relying on data from a single distributor and a limited number of products prevented the creation of a truly high-quality predictive model. As such, the most critical takeaway from the research is that reliance on the new data and attention to the continuously increasing

variety of variables and data sources are the keys to successful and efficient inventory management.

Overall, the conclusion to this thesis is that inventory management is a compromise between various factors and circumstances present. In this regard, the data science and the use of the machine learning algorithms act as the tools to get a deeper understanding of the situation with inventory and product sales, and therefore, to have a reference point for measuring and managing the level and types of risks. More importantly, the machine learning models, when employed properly, can provide a much higher level of foresight capability, future-proofing the algorithms and business strategies in an age of shifting market trends and changing customer preferences. It is hoped that the research conducted here can lead the way for more similar projects in the future, and that the insights found in this thesis can light the way toward ever more sophisticated and intelligent inventory management practices for businesses.

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