*Research Article*

# AI-Driven Pricing Algorithms for Efficient Inventory and Cost Management in Retail

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## Abstract

*This paper discusses the creation and application of a software that uses AI for pricing and stock management, aimed at improving Koçtaş's pricing strategy and inventory management. The software uses advanced machine learning techniques to examine past sales data, inventory levels, and market conditions, allowing for real-time adjustments to pricing. Integrating the AI system with Koçtaş's current analytical platform improves pricing accuracy, decreases excess stock, and lessens reliance on outside services. This paper discusses the methods used to build the system, covering aspects such as data collection, model development, and system integration. This system greatly simplifies Koçtaş's pricing processes, minimizes manual errors, and enhances operational efficiency. The software helps improve stock management by decreasing excess inventory, especially for delisted products and those with high SGS values. It also optimizes pricing strategies according to real-time market conditions. Additionally, the system's capability to adjust to market changes helps Koçtaş stay competitive in the retail industry. The paper discusses future improvements, such as refining machine learning models for better accuracy, adding more features* *to the system, and enhancing scalability and user interface design. This study shows the potential of AI in today's retail pricing and inventory management.*

**Keywords:** Dynamic Pricing, Machine Learning, Data-Driven Decision Making, Price Optimization, Retail Inventory Management

## 1. Introduction

The retail sector has seen significant transformations in recent years, driven by advancements in technology, consumer behavior shifts, and the increasing need for businesses to optimize their operational efficiency. One area where such transformation is particularly critical is in the pricing of products. Traditional pricing strategies, which often rely on manual adjustments and external service providers, are increasingly seen as inefficient and prone to error. In response to these challenges, businesses are turning to innovative solutions, with artificial intelligence (AI) and machine learning (ML) technologies emerging as key enablers in reshaping product pricing processes (Ahmad, Zilles, Hamilton, & Dosselmann, 2016; Sousa, Manuela Gonçalves, & da Costa Freitas, 2024; Kaneko & Yada, 2016; Adetunji et al., 2022).

The project at hand addresses the need for a more dynamic, accurate, and automated pricing system. This project aims to create an AI-driven software solution for product pricing in the retail sector, specifically tailored for Koçtaş, a prominent player in the Turkish retail market. By leveraging advanced AI and ML techniques, the software will optimize pricing strategies and improve stock management, particularly focusing on delisted products and products with high sales day stock (SGS) values.

The primary goal of this project is to replace traditional pricing methods, which often require manual intervention and are dependent on external service providers, with an automated and intelligent pricing system. The software will use historical sales data, product stock levels, cost information, and market trends to calculate optimal discount prices for products. This will help reduce excess inventory, minimize losses, and improve overall profit margins. By automating these pricing decisions, the system will also significantly reduce human error, which is a common issue in manual pricing processes.

Additionally, this AI-based pricing tool will bring several operational benefits to Koçtaş, such as enhanced control over pricing decisions and the elimination of reliance on external services. It will allow the company to adapt more quickly to changing market conditions and consumer demands. The integration of AI into the pricing process will also foster a culture of innovation within Koçtaş, with knowledge transfer taking place between internal teams, particularly in the areas of IT and business units. This will contribute to the development of in-house expertise and the strengthening of the company's competitive position in the market.

Furthermore, the software will be integrated into Koçtaş's existing analytical platform, ensuring seamless compatibility and allowing for real-time price updates based on various criteria, such as sales performance and stock levels. This will not only improve the speed and accuracy of pricing decisions but will also provide a more flexible and responsive pricing structure that can adapt to different product categories, stores, and market conditions.

In summary, the project will deliver a state-of-the-art AI-based product pricing software solution that will optimize Koçtaş's pricing strategy, reduce operational costs, and enhance profitability. The expected outcome is a more efficient and automated pricing system that can respond to market dynamics quickly and accurately, giving Koçtaş a competitive edge in the retail sector.

## 2. Literature Survey

Retail pricing strategies have changed significantly, especially with the use of artificial intelligence (AI) and machine learning (ML). Traditional pricing methods, which were usually set manually and remained unchanged, struggled to adapt to the fast-changing nature of today's markets. The initial models primarily relied on cost-based pricing, which involved setting prices according to production costs along with a fixed markup. This approach did not consider more complex factors such as consumer behavior, competition, or changes in demand over time. As time passed, retailers started using more flexible pricing models, like value-based and competition-based pricing. These models provided a clearer view of market dynamics but still did not offer the necessary adaptability and scalability for rapidly changing industries. With the integration of talking avatars in retail platforms, AI can enhance customer engagement, providing real-time feedback that further informs dynamic pricing strategies (Venigandla et al., 2023; Rafiei Oskooei et al., 2024; Oosthuizen et al., 2021).

AI and ML technologies have changed pricing strategies by allowing for real-time decisions based on data. These technologies enable retailers to utilize large quantities of data, including consumer buying habits, competitor prices, and market trends, which assists them in making better, more flexible pricing choices. AI-driven pricing systems can change prices automatically according to these factors, helping businesses to adjust their pricing to match the latest market conditions. Dynamic pricing enables retailers to adjust prices for each customer, taking into account factors such as browsing history, purchase intent, or geographic location. This approach helps ensure that prices remain relevant and competitive (Chen, Yang, & Xu, 2021; Yang, Feng, & Whinston, 2022; den Boer & Keskin, 2022).

Machine learning has shown to be very useful in improving these pricing strategies. Machine learning systems use algorithms that analyze past data to predict future demand and adjust prices as needed. By regularly examining patterns and trends, these systems can adjust pricing decisions in real-time. This helps businesses increase their revenue potential while reducing the chances of lost sales from pricing mistakes. Moreover, machine learning can assist retailers in determining the best pricing for promotional offers, discounts, and product bundles, which can enhance customer satisfaction and boost sales (Ban & Keskin, 2021; Bharadiya, 2023).

Additionally, AI has shown its usefulness in managing inventory, especially in improving markdown pricing. Retailers can utilize AI to find the best time and price for discounting products, helping to clear inventory while minimizing revenue loss. Timely price adjustments are crucial for businesses that handle perishable goods or seasonal products, as they can determine whether a product sells or remains unsold. The ability of AI to monitor and predict changes in demand allows retailers to foresee market trends and modify their pricing strategies ahead of their competitors, providing them with a competitive advantage (Kondapaka, 2021; Jauhar et al., 2024).

Nonetheless, implementing AI-driven pricing strategies comes with its own set of challenges. Integrating AI into current retail systems usually needs considerable upgrades to infrastructure, training for staff, and investment in technology. Smaller businesses, especially, might struggle to afford and put into place these advanced systems. There are also concerns about the ethical aspects of AI-based pricing, especially related to the possibility of price discrimination or unfair pricing practices. It is important to address the risk of reinforcing existing biases related to customer demographics or location. Failing to do so could lead to alienating consumers or attracting regulatory attention (Richards, Liaukonyte, & Streletskaya, 2016; Pandey & Caliskan, 2021). The research indicates that AI and machine learning are changing the retail industry, especially regarding pricing. These technologies allow retailers to change prices in real-time, manage inventory more effectively, and provide tailored experiences for customers, resulting in higher profits and greater customer satisfaction. To fully take advantage of these benefits, retailers need to address technical and ethical challenges while making sure that AI tools are integrated carefully and effectively into their operations. As AI develops further, its influence on pricing strategies is expected to grow, providing retailers with new opportunities to improve their methods and remain competitive in a more complex market.

For the development of the software within this project, software quality, testing processes, and user satisfaction are crucial factors to ensure success. In this context, the role of human factors in software quality has been systematically studied, with particular emphasis on evaluating the impact of users on software processes (Güveyi, Aktas, & Kalipsiz, 2020). Methodologies such as code clone detection have provided significant advantages in reducing maintenance costs and identifying errors early in the development lifecycle, ensuring more robust software systems (Aktas & Kapdan, 2016). Furthermore, deep learning-based approaches have proven instrumental in automating test scenario generation and enhancing software testing processes (Oz, Kaya, Olmezogullari, & Aktas, 2021; Oguz, Oz, Olmezogullari, & Aktas, 2022). To make testing processes more effective, methods like Hidden Markov Models, which learn from user behaviors, have been employed to optimize test scenarios through a user-centered approach. This methodology has been particularly beneficial in accelerating testing processes in large-scale software projects, significantly contributing to overall software quality (Erdem, Oguz, Olmezogullari, & Aktas, 2021). Big data analytics and recommendation systems have also emerged as key areas for enhancing software testing and evaluation. For example, recommendation systems that predict user needs facilitate more user-focused solutions during software development (Düzen & Aktas, 2016). Scalable big data testing frameworks in domains like e-commerce and e-science have effectively improved the accuracy of recommendation systems, demonstrating the significant potential of these approaches (Uzun-Per, Can, Gurel, & Aktas, 2022). While prior work primarily centers on testing methodologies to enhance software quality and user engagement, this research shifts the focus toward leveraging these principles to optimize pricing strategies and inventory management, directly addressing retail-specific challenges. This innovative application bridges a gap in the literature by demonstrating how software quality and testing practices can be extended to improve operational efficiency and competitiveness in the retail sector. Recent advancements in AI-driven technologies have revolutionized diverse fields. Studies on enhancing image resolution through generative adversarial networks (Yildiz, 2022a), efficient text classification on imbalanced datasets (Yıldız, 2022b), and metrics for abstractive summarization evaluation (Briman & Yildiz, 2024) showcase the potential of machine learning techniques. Applications of reinforcement learning for intrusion detection (Saad & Yildiz, 2022) and boosting online advertising click-through rates (Haider & Yildiz, 2023) highlight the versatility of reinforcement learning. Additionally, bitmap index optimization for high-performance queries (Yildiz, 2021) and exploring hyperparameter effects on word embedding quality (Yildiz & Tezgider, 2020) have significantly advanced computational efficiency and model performance. Unlike these studies focusing on enhancing algorithmic or methodological performance, this research integrates AI-driven dynamic pricing and inventory management into retail, directly addressing operational challenges. The system uniquely bridges theoretical advancements with practical applications by employing real-time data for pricing adjustments and inventory optimization, ensuring improved responsiveness and competitive positioning in the retail sector. This project integrates the principles of software quality and user-centered optimization to develop an AI-based pricing and inventory management system tailored for Koçtaş. Unlike previous research, which often focuses on standalone components, this study emphasizes a unified approach, combining advanced machine learning algorithms, big data analytics, and user-focused methodologies. The AI-driven pricing software dynamically adjusts product prices based on historical sales, stock levels, and market trends, aligning with Koçtaş's operational and strategic objectives. By automating the pricing process and integrating advanced testing methodologies, the project bridges theoretical advancements with practical applications, ensuring robust, efficient, and adaptive solutions for the retail sector.

## 3. Methodology

The methodology for the development of the AI-based product pricing software for Koçtaş revolves around several phases, from data collection and preprocessing to model training and integration. This approach ensures that the software can automate the pricing process while considering various factors such as product cost, market demand, and competitive pricing dynamics.

The first phase involves data gathering and integration. The software will rely on a comprehensive set of data from multiple platforms, primarily stored on Microsoft Azure Synapse. This data includes product details, sales history, inventory levels, and cost movements. A crucial task in this phase is to combine these datasets from various sources into a unified format. The data will be used to create a feature vector for each product, which serves as the basis for machine learning model development. Next, feature engineering and pre-processing are performed. The raw data is filtered and transformed into structured information suitable for algorithmic processing. The key attributes include product categories, previous discount rates, stock levels, sales trends, and SGS values (Sales Days Stock). This step involves filtering out irrelevant data and ensuring consistency across various data sources.

Once the data is prepared, the project proceeds to model development. At this stage, machine learning algorithms, particularly Long Short-Term Memory (LSTM) networks, are applied to predict future pricing trends based on historical sales and market conditions. LSTM models are particularly suitable for this type of time-series prediction due to their ability to retain information from previous time steps, making them effective for dynamic pricing predictions. The model is trained using historical sales and pricing data, and once it is capable of making accurate predictions, it undergoes evaluation and optimization. The model's performance is assessed using metrics such as Mean Absolute Percentage Error (MAPE). If the model's prediction accuracy does not meet the predefined thresholds, adjustments are made to improve its predictions. The algorithms undergo iterative improvements, enhancing their ability to handle different scenarios, such as fluctuating demand or supply chain disruptions.

The next phase involves algorithm implementation within the pricing software. The algorithms are designed to dynamically calculate product prices based on the most current data. This includes incorporating discount tiers and applying dynamic pricing rules, where discounts are automatically adjusted based on SGS values. For example, products with SGS values below 360 will not be priced below cost, while those with SGS values between 360 and 720 can accept a 10% margin reduction, and those with SGS above 720 can go up to 20%. The dynamic pricing mechanism ensures that the pricing aligns with both business objectives and market conditions.

After algorithm integration, the software is subjected to testing and validation. This phase involves rigorous testing to ensure that the pricing logic is functioning as expected, and that the system can handle data integration and dynamic updates without errors. Test cases are designed to simulate various real-world scenarios to validate the software's robustness.

Finally, the project enters the deployment and live monitoring phase. The system is deployed in a live environment, where it automatically generates clearance prices and displays them on dashboards. This dashboard, powered by PowerBI, provides real-time insights into product pricing, margin changes, and stock movements, allowing managers to make informed decisions. The pricing software is set to update prices autonomously every week, reducing manual intervention and increasing operational efficiency.

In conclusion, the methodology for this project emphasizes creating an integrated, automated, and dynamic pricing system that uses AI and machine learning to optimize pricing strategies. Through data integration, feature engineering, and algorithm development, the software will not only automate the pricing process but also adapt to ever-changing market conditions, improving both the accuracy and efficiency of pricing decisions at Koçtaş.

## 4. Expected Outputs and Benefits

The expected outputs and benefits of this project will be multifaceted, primarily focusing on enhancing Koçtaş's pricing strategies, optimizing stock management, and automating pricing processes. The key expected output is the development of an AI-based product pricing software, which will enable dynamic, data-driven pricing decisions based on past sales data, market trends, and product-specific variables. This software will calculate optimal discount prices for delisted products and those with high SGS values, ensuring that prices align with market conditions and cost constraints.

One significant benefit is the reduction of manual errors in the pricing process. By automating price calculations and incorporating machine learning models, the software will reduce human intervention, increasing accuracy and efficiency in pricing decisions. This automation will save considerable time and effort, which was previously spent on manual price setting, thereby improving operational efficiency and reducing labor costs.

Another benefit is the optimization of stock management. By aligning pricing with demand and stock levels, the software will help reduce excess inventory and improve the turnover of products with high SGS values. This will lead to more efficient stock rotation, minimized overstocking, and reduced storage costs. Furthermore, the system will provide real-time updates on prices, which will enhance the company's responsiveness to market fluctuations and competitor pricing.

The development of internal expertise is another expected benefit. The transition from outsourcing the pricing process to developing it in-house will lead to valuable knowledge transfer within Koçtaş's Information Technology and business teams. This will foster a deeper understanding of pricing algorithms and reduce dependency on external service providers.

Overall, this project will not only improve pricing accuracy and profitability but also strengthen Koçtaş's competitive position by providing the ability to quickly adapt to market changes, ensuring sustainability in a dynamic retail environment.

## 5. Results and Future Work

The creation of the AI-based pricing software has made notable advancements in improving Koçtaş's pricing and inventory management systems. The software analyzes past sales data, inventory levels, and market conditions, enabling the adjustment of product prices in real-time. This has improved pricing accuracy and helped reduce excess stock, especially for delisted products and those with high SGS values. Additionally, automating the pricing process has decreased manual errors, lowered reliance on outside services, and simplified decision-making within the company.

The project has brought significant improvements in operational efficiency, as the pricing process is now managed automatically, which saves a lot of time and resources. The integration of the system with Koçtaş's analytical platform has allowed the company to react more swiftly to changing market conditions, thereby enhancing its competitive position.

In the future, the software will keep improving as additional data is added and as machine learning models are adjusted for better accuracy in predicting prices. Future work will aim to broaden the system's functions, increase its scalability, and improve its ability to adjust to various market situations. Moreover, we will focus on improving the user interface and incorporating more forecasting tools.

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## References

[1] Ahmad, H. W., Zilles, S., Hamilton, H. J., & Dosselmann, R. (2016). Prediction of retail prices of products using local competitors. *International Journal of Business Intelligence and Data Mining*, *11*(1), 19-30.

[2] Sousa, C., Manuela Gonçalves, A., & da Costa Freitas, A. (2024, July). Categories's Churn: A Machine Learning Approach in Retail. In *International Conference on Computational Science and Its Applications* (pp. 319-336). Cham: Springer Nature Switzerland.

[3] Kaneko, Y., & Yada, K. (2016, December). A deep learning approach for the prediction of retail store sales. In *2016 IEEE 16th International conference on data mining workshops (ICDMW)* (pp. 531-537). IEEE.

[4] Adetunji, A. B., Akande, O. N., Ajala, F. A., Oyewo, O., Akande, Y. F., & Oluwadara, G. (2022). House price prediction using random forest machine learning technique. *Procedia Computer Science*, *199*, 806-813.

[5] Venigandla, K., Vemuri, N., Thaneeru, N., & Tatikonda, V. M. (2023). Leveraging AI-Enhanced Robotic Process Automation for Retail Pricing Optimization: A Comprehensive Analysis. *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)*, *2*(2), 361-370.

[6] Rafiei Oskooei, A., Yahsi, E., Sungur, M., & S. Aktas, M. (2024, July). Can One Model Fit All? An Exploration of Wav2Lip's Lip-Syncing Generalizability Across Culturally Distinct Languages. In *International Conference on Computational Science and Its Applications* (pp. 149-164). Cham: Springer Nature Switzerland.

[7] Oosthuizen, K., Botha, E., Robertson, J., & Montecchi, M. (2021). Artificial intelligence in retail: The AI-enabled value chain. *Australasian Marketing Journal*, *29*(3), 264-273.

[8] Chen, L., Yang, Y., & Xu, Q. (2021). Retail dynamic pricing strategy design considering the fluctuations in day-ahead market using integrated demand response. *International Journal of Electrical Power & Energy Systems*, *130*, 106983.

[9] Yang, C., Feng, Y., & Whinston, A. (2022). Dynamic pricing and information disclosure for fresh produce: An artificial intelligence approach. *Production and Operations Management*, *31*(1), 155-171.

[10] den Boer, A. V., & Keskin, N. B. (2022). Dynamic pricing with demand learning and reference effects. *Management Science*, *68*(10), 7112-7130.

[11] Ban, G. Y., & Keskin, N. B. (2021). Personalized dynamic pricing with machine learning: High-dimensional features and heterogeneous elasticity. *Management Science*, *67*(9), 5549-5568.

[12] Bharadiya, J. P. (2023). Machine learning and AI in business intelligence: Trends and opportunities. *International Journal of Computer (IJC)*, *48*(1), 123-134.

[13] Kondapaka, K. K. (2021). AI-Driven Inventory Optimization in Retail Supply Chains: Advanced Models, Techniques, and Real-World Applications. *Journal of Bioinformatics and Artificial Intelligence*, *1*(1), 377-409.

[14] Jauhar, S. K., Jani, S. M., Kamble, S. S., Pratap, S., Belhadi, A., & Gupta, S. (2024). How to use no-code artificial intelligence to predict and minimize the inventory distortions for resilient supply chains. *International Journal of Production Research*, *62*(15), 5510-5534.

[15] Richards, T. J., Liaukonyte, J., & Streletskaya, N. A. (2016). Personalized pricing and price fairness. *International Journal of Industrial Organization*, *44*, 138-153.

[16] Pandey, A., & Caliskan, A. (2021, July). Disparate impact of artificial intelligence bias in ridehailing economy's price discrimination algorithms. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 822-833).

[17] Guveyi, E., Aktas, M. S., & Kalipsiz, O. (2020). Human factor on software quality: A systematic literature review. In O. Gervasi, B. Murgante, S. Misra, C. Garau, I. Blečić, D. Taniar, B. O. Apduhan, A. M. A. C. Rocha, E. Tarantino, C. M. Torre, & Y. Karaca (Eds.), Computational Science and Its Applications – ICCSA 2020. Lecture Notes in Computer Science (pp. 918–930). Springer.

[18] Aktas, M. S., & Kapdan, M. (2016). Structural code clone detection methodology using software metrics. International Journal of Software Engineering and Knowledge Engineering, 26(2), 307–332.

[19] Oz, M., Kaya, C., Olmezogullari, E., & Aktas, M. S. (2021). On the use of generative deep learning approaches for generating hidden test scripts. International Journal of Software Engineering and Knowledge Engineering, 31(10), 1447–1468.

[20] Oguz, R.F., Oz, M., Olmezogullari, E., Aktas, M. S. (2022). Extracting Information from Large Scale Graph Data: Case Study on Automated UI Testing, Euro-Par 2021: Parallel Processing Workshops, LNCS, volume 13098.

https://doi.org/10.56038/ejrnd.v4i4.607


[21] Uzun-Per, M., Can, A. B., Gurel, A. V., & Aktas, M. S. (2021). Big data testing framework for recommendation systems in e-science and e-commerce domains. 2021 IEEE International Conference on Big Data (Big Data), 2021.

[22] Erdem, I., Oguz, R. F., Olmezogullari, E., & Aktas, M. S. (2021). Test script generation based on hidden Markov models learning from user browsing behaviors 2021 IEEE International Conference on Big Data (Big Data), 2021.

[23] Düzen, Z., & Aktas, M. S. (2016). An approach to hybrid personalized recommender systems. 2016 International Symposium on INnovations in Intelligent SysTems and Applications (INISTA), 2-5 Ağustos 2016, Sinaia, Romanya.

[24] Uzun-Per, M., Gurel, A. V., Can, A. B., & Aktas, M. S. (2022). Scalable recommendation systems based on finding similar items and sequences. Concurrency and Computation: Practice and Experience, 34(20).

[25] Yildiz, B. (2022, September). Enhancing image resolution with generative adversarial networks. In 2022 7th International Conference on Computer Science and Engineering (UBMK) (pp. 104–109). IEEE.

[26] Yıldız, B. (2022). Efficient text classification with deep learning on imbalanced data improved with better distribution. Turkish Journal of Science and Technology, 17(1), 89–98.

[27] Briman, M. K. H., & Yildiz, B. (2024). Beyond ROUGE: A comprehensive evaluation metric for abstractive summarization leveraging similarity, entailment, and acceptability. International Journal on Artificial Intelligence Tools.

[28] Saad, A. M. S. E., & Yildiz, B. (2022, September). Reinforcement learning for intrusion detection. In International Conference on Computing, Intelligence and Data Analytics (pp. 230–243). Cham: Springer International Publishing.

[29] Haider, U., & Yildiz, B. (2023, December). A novel use of reinforcement learning for elevated click-through rate in online advertising. In 2023 International Conference on Computational Science and Computational Intelligence (CSCI) (pp. 64–70). IEEE.

[30] Yildiz, B. (2021). Optimizing bitmap index encoding for high performance queries. Concurrency and Computation: Practice and Experience, 33(18), e5943.

[31] Yildiz, B., & Tezgider, M. (2020). Learning quality improved word embedding with assessment of hyperparameters. In Euro-Par 2019: Parallel Processing Workshops: Euro-Par 2019 International Workshops, Göttingen, Germany, August 26–30, 2019, Revised Selected Papers 25 (pp. 506–518). Cham: Springer International Publishing.