**American University Kyiv**

A Capstone Project

# THE ROLE OF MACHINE LEARNING-DRIVEN SOLUTIONS IN ENHANCING MANAGERIAL DECISION-MAKING IN THE RETAIL INDUSTRY

РОЛЬ МАШИННОГО НАВЧАННЯ ЯК ІНСТРУМЕНТУ В ПОКРАЩЕННІ УПРАВЛІНСЬКИХ РІШЕНЬ У ГАЛУЗІ РОЗДРІБНОЇ ТОРГІВЛІ

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## ABSTRACT

Traditionally, data processing in the retail industry heavily relies on manual methods or situational sampling, often affected by human factors such as data manipulation or falsified photo reports to hide poorly executed tasks. The purpose of this research is to analyze the practical impact of implementing machine learning (ML) technologies on enhancing managerial decision-making and business process transformation in the Ukrainian retail sector.

The research aims to answer the question: How do ML-driven solutions improve the quality and efficiency of managerial decision-making in the Ukrainian retail sector? Hence, the project involved the Confectionery Corporation “Roshen” and its 20 subsidiary distributors to conduct the study and answer the stated question. Mix of quantitative and qualitative methods have been utilized in the project to assess the implementation and performance of ML-driven solutions. Based on the results of this implementation, the adoption of ML solutions optimized personnel management, improved analysis and evaluation of merchandising performance, minimized manipulations, and automated processes, thereby enhancing the quality of managerial decision-making in Confectionery Corporation “Roshen” and its 20 subsidiary distributors.

The findings of the research highlight the efficiency of ML-driven solutions and show their potential for other areas such as sales forecasting of new products and marketing research. Future research should focus on enhancing automatization of current solution and exploring additional opportunities for leveraging ML to optimize business operations, reducing operational costs and strengthen competitive positioning in the retail sector.


*Keywords: machine learning, managerial decision-making, retail digital transformation, business process automation.*

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## INTRODUCTION

The efficiency of managerial decision-making in the retail industry can be attributed to key factors: efficient management approaches and leveraging technologies. The findings of the work  showed that a balanced approach to both yields better results. The rapid grow of machine learning technologies has fundamentally altered the landscape of managerial decision-making, particularly in industries driven by large-scale data, such as retail. ML has been recognized for its ability to enhance decision-making by transforming complex datasets into actionable insights, thereby improving efficiency, accuracy, and strategic foresight (Davenport Harris, 2017;). However, while the adoption of ML in retail has garnered significant attention globally, the extent to which it influences managerial decision-making in specific regional markets, such as Ukraine, remains underexplored (Kovalchuk, 2023). Many researchers, Smith et al. (2020), Nguyen and Duong (2021) focus heavily on operational applications, such as supply chain optimization and personalized marketing, with less emphasis on how ML-driven insights directly impact managerial decision-making processes. While ML offers immense potential for predictive analytics, fraud detection, and customer segmentation, its adoption faces challenges such as high implementation costs, data privacy concerns, and resistance to change within organizations (Jain & Kumar, 2022; Large Language Models AI. 2024). Furthermore, decision-makers often lack the technical expertise required to interpret complex ML insights, which can hinder the effective utilization of these tools (Zou & Schiebinger, 2018). These challenges underscore the importance of understanding both the opportunities and limitations of ML-driven decision-making in real-world contexts.

The conducted literature review highlights the need for the practical implications of ML in enhancing decision-making within the Ukrainian retail sector. To address the identified literature gap, the purpose of the research is present and evaluate the practical implementation the impact of ML-driven solutions on managerial decision-making in the retail sector. The subject of the study is the Confectionery Corporation "Roshen" and its 20 subsidiary distributors. The object of this research is to analyze how ML can enhance managerial decision-making processes in the retail industry of Ukraine.

To achieve the stated purpose the author settled the following tasks:

– understand how ML integrates into managerial decision-making frameworks in large retail corporations; provide an overview ML in retail industry;

– discover adoption of ML solution by domestic and international corporations;

– conduct a detailed case study analysis of the Confectionery Corporation "Roshen" and its subsidiary distributors;

– observe and analyze the impact of ML-driven solutions on key decision-making metrics;

– assess the implications of ML adoption on organizational performance in the retail sector, present outcomes of economic analysis of ML-driven solutions for optimization of personnel management in Confectionery Corporation "Roshen";

– and propose potential improvements and identify limitations in ML-driven decision-making applications.

The relevance of the chosen topic can be emphasized by noting its direct impact on solving the problems of inefficiency and selectivity of management decision-making in the retail sector by utilizing ML solutions. Focusing on the Ukrainian retail industry, this study provides practical insights into how the use of machine learning can help optimize operations, increase the speed of management decisions. Additionally it can  address region-specific problems such as data manipulation and resource constraints, thus narrow critical gaps in academic literature and industry practice.

The study utilized a mixed-methods approach, in particularly, combining quantitative analysis of outcomes generated from the implementation of the ML system and qualitative views of involved  top management experts of the company's to gain a comprehensive understanding of the issues. Therefore, this research methodology enables an in-depth analysis of  how ML-driven solutions influence managerial decision-making indicators related to efficiency, accuracy and cost-effectiveness. As an in-depth case study design, the research combines theoretical findings with its practical application taking due cognizance of the role of machine learning in decision-making in retain industry.

This project is structured as follows: Chapter 1, provides an overview of the theoretical framework for managerial decision-making and explores the role and importance of machine learning in the retail industry. Chapter 2 evaluates the practical implementation of machine learning solutions in Confectionery Corporation "Roshen" , analyzing their impact on key indicators of managerial decision-making and organizational effectiveness. Chapter 3 identifies the limitations of the study and suggests potential improvements to machine learning-based solutions in retail management. The conclusion summarizes the findings, discusses implications for future research and practice, and addresses the limitations of our literature review.

This research makes two main contributions. First, it bridges the identified knowledge gap by providing empirical evidence on the role of ML in managerial decision-making within the

Ukrainian retail sector, an area that has received limited attention in prior studies. Second, it offers practical recommendations for overcoming the challenges associated with ML adoption, thereby supporting organizations in leveraging these technologies to enhance decision-making and operational performance. Hence, the study not only addresses critical gaps in the literature but also provides a roadmap for retail corporations seeking to effectively integrate ML tools for strategic advantage.

# CHAPTER 1. THE ROLE AND IMPORTANCE OF MACHINE LEARNING IN MANAGERIAL DECISION-MAKING

## 1.1 The framework for managerial decision-making process in large retail corporations

The retail industry is undergoing a profound transformation driven by artificial intelligence (AI) and ML technologies, which are reshaping decision-making processes at scale. Machine learning, a subset of AI, enables systems in the retail industry to autonomously analyze data, identify patterns, and derive actionable insights for continuous improvement.

The emergence of machine learning has formed one of the powerful channels through which businesses can transform their performance. In retail companies, ML is critical in making the right decisions that help optimize operations, improve the quality of the customer experience, and enhance the efficiency of the corporation. The potential application area for ML is predictive analytics, pattern recognition, and data-driven insight in revolutionizing managerial decision-making processes.

The power of data is crucial for domestic and international retail corporations in their ongoing business operations. Corporations have effectively manage extensive related data sets. This data stores information related to customer preferences, inventory positions and market trends. Traditionally, decision-makers use historical analysis for decision making process. However, due to the increase in complexity of related retail operations, where real-time responses have become critical, the traditional approaches are no longer efficient. ML solutions offer prediction capabilities that allow analysts and decision makers  to predict trends, risks, and sensitive decisions before time. Therefore, utilization of ML tools for decision making process leads to unlocking the full potentials of data and achieve significant business growth for corporations.

Machine learning, a subset of AI, enables systems in the retail industry to autonomously analyze data, identify patterns, and derive actionable insights for continuous improvement (McKinsey Digital. (2024). A recent survey by NVIDIA (2024) revealed that 69% of retailers already using AI reported revenue increases, with 28% achieving growth between 5% and 15% annually. At the same time, 72% of respondents experienced a reduction in operational costs, with 23% reporting savings above 15%.

More than a third of retail respondents reported that AI has directly contributed to improved decision-making in their business operations (Figure 1).

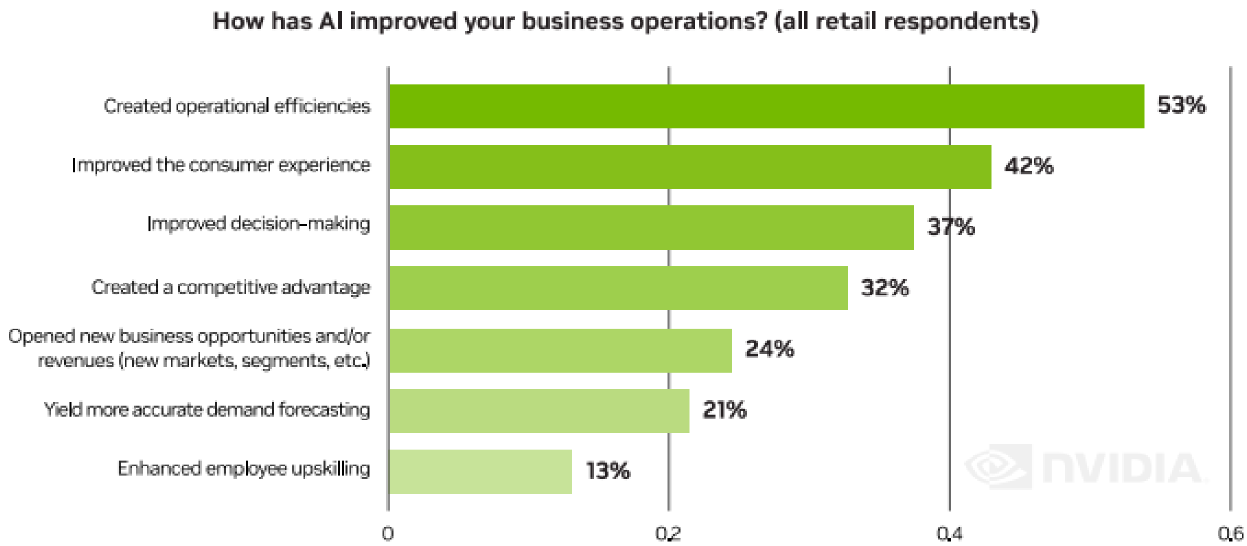



Figure 1. State of AI in Retail and CPG (2024).

Source: Data reprinted from (NVIDIA Survey Report, 2024)

The shift increasing adoption and integration of AI and ML technologies is particularly pronounced among large corporations, such as Wal-Mart Stores, Inc. and Amazon Inc, which leverage ML for supply chain optimization, demand forecasting, and personalized marketing. For instance, Wal-Mart Stores, Inc. included factor ML algorithms for supply chain optimization and customer demand forecasting (Smith et al., 2020). Ukrainian retailers like ROZETKA.UA, LLC planning to incorporate a program of ML-driven personalized marketing that boosts customer engagement (Kovalchuk, 2023).

It's worth noting that implementing ML for decision-making brings various difficulties, even though it has many advantages (Unite.ai. 2023; Appinventiv. 2023). Issues such as data privacy and high implementation costs plus resistance to change have been noticed. However, under increased competition and amidst constantly changing consumer demands, the use of ML in managerial processes is more of a necessity than an option anymore (Unite.ai. 2023; Appinventiv. 2023). This chapter discusses the general role and importance of ML in managerial decision-making within the retail sector and reviews the framework of decision-making at large retail corporations. It presents an overview of existing applications of ML in retail and examines adoption trends among domestic and international corporations.

Managerial decision-making is always structurally a well-defined process that straitly harmonizes strategic goals with operational activities in major retail corporations. More data, in terms of volume and sources within the retail industry has led to the need for an organized method of making use of insights drawn from a varied dataset. Most well-framed decision-making processes often include stages such as the identification of a problem, collecting and analyzing data, generating a solution, implementing a solution, and evaluating the solution (Davenport & Harris, 2017). Primarily, the retail sector decisions relate to pricing strategies, inventory management, and marketing and customer services.

Machine learning in managerial decision-making process could be responsible for unifying the framework at which it strengthens the said steps accordingly. The ML model processes a large set of heterogeneous datasets from different sources, such as sales systems, customer feedback, and market trends. This unearths many latent patterns that managers can use to predict customer preferences or any supply chain disruption. For example, many international retail corporations uses machine learning-driven forecasting tools to predict customer demand during the holidays, to ensure that there is minimal out-of-stock inventory. The same is true for Ukrainian retailers, for example, large supermarket chains, uses ML for demand forecasting and optimization of its loyalty program, which ensures proper allocation of resources in serving and keeping customers happy. All these together highlight the needs of corporations to shift from passive to active management and improves efficiency at the operational and strategic levels.

## 1.2 Overview of ML in the Retail Industry

Machine learning is a technology that enables machines and systems to analyze massive volumes of data, identify patterns, and essentially teach themselves to make effective decisions. Within the retail domain, ML finds wide adoption in business process optimization, enhanced customer service, and enhanced competitiveness of companies (Appinventiv. 2023, Itransition. 2022).

The key machine learning models applied to retail include classification, regression, and clustering models, along with deep learning algorithms for image recognition, text processing, and generative models. Modern ML technologies actively used in retail include (Nisum, 2023):

- Computer vision is used to automate the recognition of products on shelves, track inventory, and check compliance with display standards.
- Generative AI is creating personalized content, such as product descriptions, advertising materials, or recommendations for customers.

- Natural language processing (NLP) is used in chatbots, voice assistants, and to analyze customer feedback. Recommendation systems — personalize offers to customers based on their behavior and purchase history.
- Predictive models is demand forecasting, inventory management, and price optimization based on demand, competition, or seasonality.
- Dynamic pricing systems is adapt prices in real time to maximize profits.

Utilising ML, retail companies can forecast product demand, personalize recommendations for customers, optimize inventory management, automate pricing, and detect fraudulent transactions. For example, ML algorithms help analyze customer behavior to predict their needs or create effective marketing campaigns based on a personalized approach (GeeksforGeeks, 2023).

However, it is important to admit that not all companies are able to implement ML solutions due to the high complexity and cost of their implementation and maintenance. Successful use of such technologies requires at least one highly qualified specialist who can integrate these tools with the company's business strategy. This specialist must understand how to combine the technical capabilities of ML with the vision of the company, taking into account its specific goals and resources. Thus, ML opens up new horizons for the retail industry, but its effective use depends on the willingness of companies to invest in infrastructure, staff training and integration of technology into business processes.

The retail industry has become a prominent arena for the application of machine learning, with businesses increasingly relying on data-driven insights to meet consumer expectations, optimize operations, and stay competitive. ML's versatility allows it to address a wide range of challenges and opportunities, from enhancing customer experiences to streamlining supply chain management (Financial Times, 2024).

According to the NVIDIA's (2024) survey, 69% of retailers using ML reported revenue increases, while 72% achieved operational cost reductions. ML applications in areas like store analytics, personalized recommendations, and supply chain optimization have demonstrated measurable benefits. Retailers employing six or more ML use cases experienced the highest impact, showcasing the scalability of these technologies in diverse operational contexts.

The Statista (2024) reported that retailers who adopting AI and ML technologies have experienced a substantial competitive edge (Figure 2).

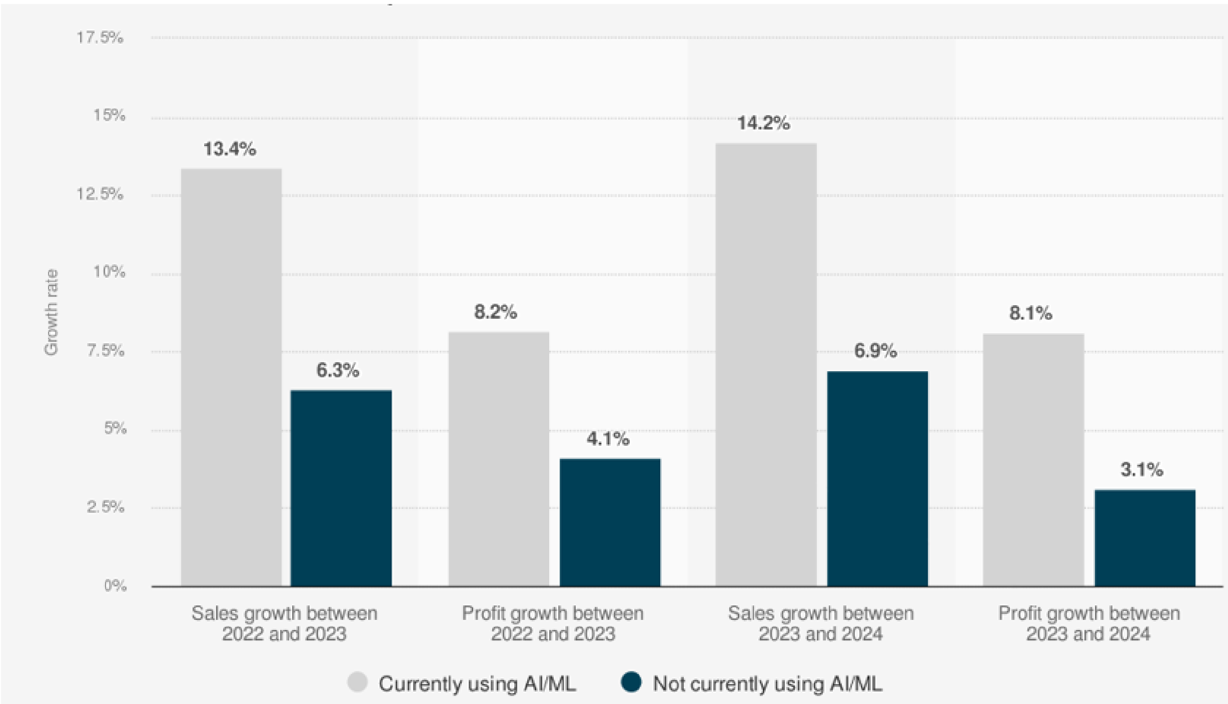



Figure 2. Impact of AI and ML usage on retail performance (2022 – 2024).
Source: Data reprinted from (Statista, 2024)

As ML adoption grows, retailers are focusing on advanced technologies like generative AI and computer vision. These innovations are expected to enhance areas such as augmented reality shopping and autonomous stores. However, challenges such as high implementation costs, data privacy concerns, and a lack of skilled AI professionals remain barriers to widespread adoption. The NVIDIA's report found that 64% of retailers plan to increase their AI infrastructure investments over the next 18 months, signaling a strong commitment to overcoming these hurdles.

ML is revolutionizing the retail industry by enabling data-driven decisions that enhance efficiency, improve customer satisfaction, and drive profitability. Its applications span from operational optimization to innovative customer interactions, solidifying its role as a critical technology in the evolving retail landscape. As retailers continue to embrace ML, the focus will shift toward maximizing its potential while addressing the associated challenges, ensuring sustainable growth in a competitive market.

## 1.3 Adoption of ML Solutions by Domestic and International Corporations

Recalling that retail is one of the sectors that has gained almost immediate uptake in the past few years. Machine learning has enabled the industry to have a strategic, data-centric, and automated operation cycle. The domain of ML applications in retail is vast and spans over customer analytics, inventory management, and sales forecasting. With ability to process and analyze large sets of data quickly, ML delivers actionable insights into improving customer experience and operations.

Recent research shows that U.S. retail companies are increasingly adopting AI technologies, with marketing automation (48.9%) leading the way, followed by virtual agents/chatbots (31.4%) and data analytics (28.6%). Key areas like machine learning (17.4%), natural language processing (20.9%), and decision-making systems (13.3%) highlight the growing reliance on AI for streamlining operations and improving customer interactions. While advanced technologies like large language models (12%) and computer vision (4.9%) are gaining traction, niche applications such as biometrics (2.5%) and augmented reality (2.1%) see limited adoption (Statista, 2024). This trend underscores the retail sector's focus on leveraging AI to enhance efficiency and competitiveness.

Personalization is one of the most prevalent applications of machine learning in retail. Companies such as Amazon.com, Inc. use ML algorithms to recommend products based on an individual user's taste and browsing history. This personal recommendation does not only enhance customer satisfaction but also increases sales. For example, Ukrainian e-commerce platform Prom.ua has used ML to customize product recommendations for improved conversion rates and customer retention (Kovalchuk, 2023).Another important area is supply chain management. Routes would be optimized, delays predicted, and operational cost reduced with ML algorithms. For instance, DHL, a logistics partner of most retail companies, leverages AI to boost the efficiency of deliveries.

The inventory management system for Wal-Mart Stores, Inc., enabled by AI, constantly updates its stocks in real-time and wastage is minimized via highly accurate demand forecasting (Smith et al., 2020). ML models can identify unusual transaction patterns, mitigating fraud risks. Retailers like eBay use AI, in this case, to detect any anomalous patterns in transactions that may be contradictory to normal behavior so as to protect against fraud and build trust among the consumers.

Ukrainian fintech services aimed at the retail sector, for example Monobank, use machine learning in fraud detection to ensure the security of their online transactions (Kovalchuk, 2023). Machine learning technologies are being further adopted with newer technological breakthroughs. Greater depth in retail operations will surely be achieved with advanced ML models, specifically deep learning and reinforcement learning that will revolutionize the industry by bringing fresh new prospects for innovation and efficiency.

Table 1 provides summary overview of key applications of ML in retail industry.

Table 1. Key applications of ML in retail industry

| Corporation | ML Solutions | Description | Outcomes |
|---|---|---|---|
| Rozetka.ua, LLC<br>Amazon.com Inc. | Personalized customer experiences | ML enables hyper-personalization, analyzing customer behavior, purchase history, and preferences to deliver tailored product recommendations. | Higher customer retention and increased sales, boost engagement and conversion rates |
| Walmart Inc.<br>H&M Hennes & Mauritz AB<br>Silpo-Food, LLC | Demand forecasting and inventory management | ML enhances forecasting accuracy by analyzing historical sales data, weather patterns, and market trends. Walmart, for instance, uses ML to predict demand, | Optimize stock levels, and minimize inventory costs, ensuring products are available when customers need them. |
| eBay Inc.<br>Silpo-Food, LLC | Fraud Detection and Loss Prevention | ML helps detect fraudulent activities and reduce shrinkage | Transaction monitoring, ensuring secure online shopping environments. |
| Rozetka.ua, LLC<br>Amazon.com Inc. | Dynamic Pricing | ML algorithms allow retailers to adjust prices in real time based on factors like demand, competition, and inventory levels. | Remain competitive and maximize profitability. |
| H&M Hennes & Mauritz AB<br>Sephora USA, Inc. | Conversational AI and Virtual Assistants | Chatbots powered by ML are transforming customer service, providing instant support across multiple languages | Virtual assistants are becoming essential in creating seamless shopping experiences, particularly for e-commerce platforms |
| Nike, Inc.<br>ASOS plc | Generative AI in Marketing and Content Creation | Generative AI is revolutionizing retail by automating content generation for advertisements, product descriptions, and multimedia campaigns. | Enhancing customer engagement while reducing operational costs |

Source: Data adapted from (Kovalchuk, 2023; Akkio, 2023; 2020; NVIDIA, 2024)

The analyzed outcomes of the Table 1 show that the levels and paces of adoption of ML solutions vary from one region to another and one scale of operations to another but indeed are indicative of the trend that exists for use by retail corporations, globally and domestically, to arm themselves with these technologies that provide a competitive edge through real-time insights and automation of decisions.

Wal-Mart, Inc. is applying supply chain optimization by serving customers better through the use of ML systems on historical sales and external factors such as weather patterns. Amazon uses AI-based engines to increase their sales as well as create customer loyalty. Within Ukraine, Rozetka.com, LLC and Silpo-Food, LLC retailers have applied ML in analyzing customer behavior, imposing dynamic pricing, and optimizing the supply chain to deliver improved operational efficiency and better customer experiences through a better run-of-stock. However, ML is not without its challenges: it requires enormous initial spending, while also inducing fears of a possible breach of information and scarcity in qualified personnel. Ukrainian IT companies are working together with retailers to build specialized ML solutions for the markets, with the backing of government initiatives that promote technological integration. The trend is further highlighted by surging investments in ML technology across the globe. Indeed, with increasing numbers of retailers turning toward ML, it will be through an enhanced decision-making process and operations that the ability of ML to sustain growth becomes essential for maintaining a competitive edge in today's increasingly competitive retail landscape.

# CHAPTER 2. EVALUATING THE IMPACT OF MACHINE LEARNING SOLUTIONS ON MANAGERIAL DECISION-MAKING PROCESS IN THE RETAIL INDUSTRY

## 2.1 Practical applications of the utilization of ML in 20 subsidiary distributors of Confectionery Corporation "Roshen"

Confectionery Corporation "Roshen" (Roshen) is one of the largest manufacturers of confectionery products in Eastern Europe, with a presence in over 30 countries worldwide. The company specializes in producing a wide range of sweets, including chocolates, candies, cakes, cookies, and wafers. Employing more than 10,000 staff, Roshen has established a strong reputation for quality and innovation, achieving annual sales exceeding $800 million. Through its network of 20 subsidiary distributors, the corporation ensures its products are available in retail outlets across key markets, focusing on delivering excellence in every aspect of its operations (Roshen Confectionery Corporation. n.d..; Wikipedia, n.d.)

Since the corporation ensures the distribution of its products to over 100,000 retail outlets, one of the primary challenges faced by Roshen was ensuring effective distribution of its products to partner retail outlets in 2022–2024. It was important to keep maintaining control over shelf availability and product placement. Availability and proper display of products are critical factors that directly impact sales. To address these needs, the company relied heavily on merchandising. This process involved distributor agents visiting retail stores, checking product availability, verifying compliance with display standards, and uploading photographic evidence to the (Enterprise resource planning (ERP) system.

However, despite strict guidelines and photo verification, three main problems emerged:

- falsification of geolocation data: agents sometimes logged visits without physically being present at the store, marking tasks as completed in the ERP system by spoofing GPS data;
- submission of outdated photos: agents uploaded photos from previous visits, misrepresenting the current status of store compliance;
- high operational costs: the manual supervision required to verify the authenticity of these reports and photos placed a significant burden on supervisors, leading to increased operational costs and inefficiencies;

- lack of automated systems to control the speed of distribution of new products across retail outlets: this made it difficult to analyze and manage the process of introducing new products to the market.
- reporting was received every few weeks: this slowed down decision-making, which could lead to lost sales due to untimely response to problems.

These issues affected sales led to higher costs associated with hiring additional personnel to oversee and verify compliance processes. Also they impacted sales and increased costs associated with hiring additional staff to monitor and verify compliance processes. Understanding the nature of these issues and their relationship to relevant machine learning archetypes (in particular, anomaly detection) allowed us to select the most appropriate algorithms and methods described in this section.

To overcome these challenges, Roshen's decision makers implemented a machine learning solution that automated the verification of store visit results and significantly reduced the workload for supervisors. The ML pipeline is visualized in Figure 3.

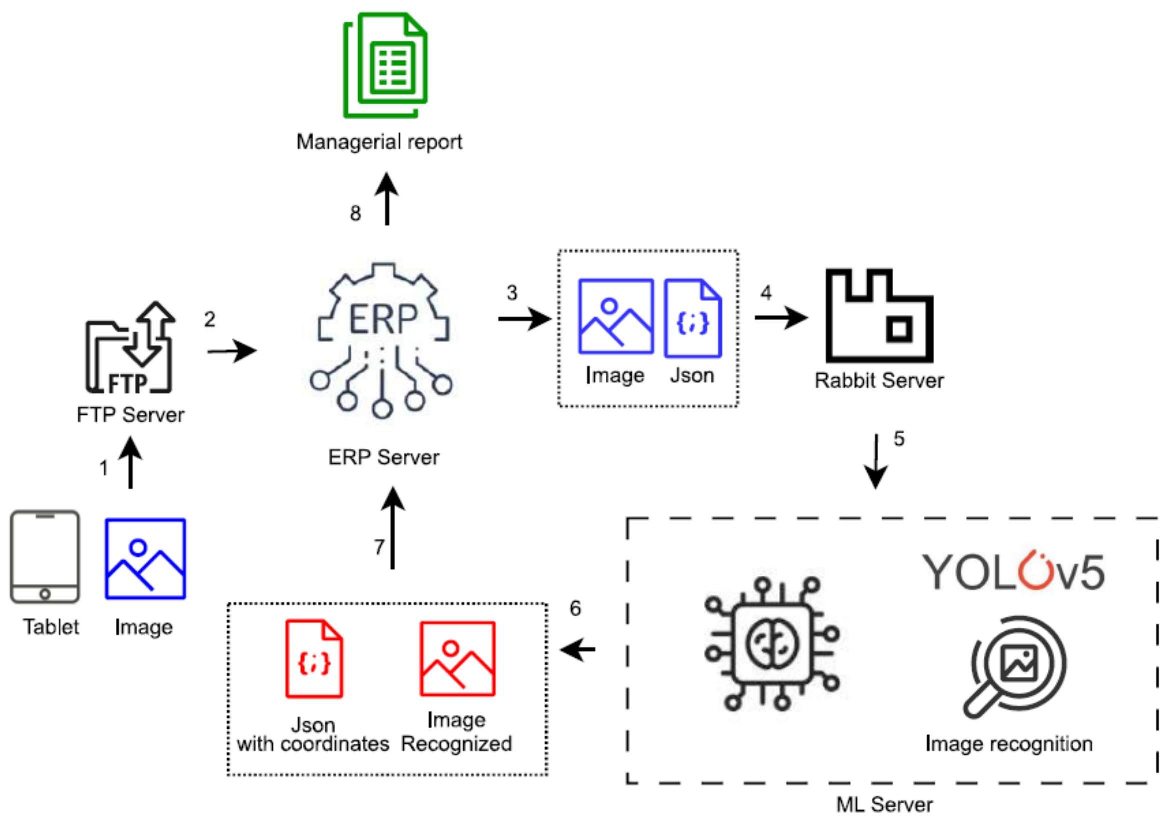



Figure 3. Machine learning solution for image recognition and managerial reporting at Roshen.

Source: Developed by author based on L. Hosudarskiy (personal communication, December 1, 2024)

The machine learning model used by Roshen requires structured and unstructured input data to ensure accuracy and efficiency. **Key input characteristics include:**

- photographic data (photo evidence of product placement uploaded via the company’s CRM application. Data type: JPEG images processed by YOLO-based object recognition algorithms);
- product metadata (reference data for all products, including SKUs, sizes, packaging type, and placement requirements. Data type: JSON for structured input);
- geolocation data (real-time GPS coordinates of agents to verify their presence at retail locations). Data type: Geospatial (latitude, longitude);
- historical sales data (past sales metrics for demand forecasting and distribution analysis for 2020-2024 years). Data type: Time series in tabular format (SQL);.
- pperational logs (merchandiser visit schedules, task completion statuses, and product delivery records). Data type: relational database records.

While, **output, based on M**L solution targets expressed in economics (business) results:

- 4% increase in sales (ensuring consistent product availability and display standards in retail locations drives sales growth);
- 20% reduction in operating costs (automating compliance and geolocation data checks minimizes manual controls and operational inefficiencies);
- eliminate data manipulation risks (improved transparency in merchandiser reporting through automatic detection of falsified data and outdated photos);
- improved staff productivity (reduced time spent manually reviewing reports by supervisors by up to 80%, allowing for resource reallocation);
- accelerated decision-making (moving from weekly to daily reports speeds up response to deviations by 70%.)

These results highlight the transformative role of ML solutions in operational and management decision-making processes simultaneously.

The backend ML solution was developed using a combination of real-time object detection algorithm YOLO, RabbitMQ message broker that implements Advanced Message Queuing Protocol, hence used as a communication between ERP system and ML solution and internal developed software, which worked seamlessly together to deliver the desired functionality.

The YOLO is real-time object detection algorithm was used to analyze images uploaded by agents. YOLO identified and classified products on store shelves, ensuring compliance with placement standards (V7 Labs, 2024; LearnOpenCV, 2024).

RabbitMQ is an open-source message broker software that facilitates communication between different applications or services by sending and receiving messages using protocols like Advanced Message Queuing Protocol (AMQP). It helps decouple systems, ensuring efficient data transfer, reliability, and scalability in distributed systems (Pivotal Software, n.d.).

This technological synergy enabled the system to process images and GPS data in real time, automate compliance assessments, and generate actionable insights for supervisors.

The **main task** of the ML solution was to verify compliance with contractual terms between store and Roshen, regarding agreed the percentage of products on store shelves. This indicator must comply with agreed contractual terms, and in case of non-compliance, Roshen can impose fines, which stimulates increased accuracy in working with distributors.

Another important ML solution's function was the automated verification of merchandisers' photo reports. Using reference photo models with reference product placement the ERP system detects deviations in product display and assesses compliance with display standards, including analysis of the assortment and placement of new products. This feature allowed Roshen assess the speed of new product distribution and compliance with key performance indicators (KPIs).

The process of the developing and implemented a ML solution at Roshen that automated the verification of store visit results has been implemented in **6 steps**, hence this method allowed the company to achieved the results presented and analyzed in the project.

**Step 1. Initiating step (collect the data).** The YOLO object recognition algorithm was used to implement the solution. Training datasets were formed using Cutter software, where photos of the product range were manually marked (Appendix D).

**Step 2. Data preparation.** The output was JSON files, which were converted to a YAML format understandable by YOLO. Then, automation in Jupyter Notebook launched the process of training models based on the prepared dataset (Figure 4).

```
dataset_path = Path('/opt/AI/infarred_data/Storage/Datasets/Rolls/Roll')
labels = sorted(dataset_path.rglob("*labels/train/*.txt")) # all data in 'labels'
yaml_file = '/opt/AI/infarred_data/Storage/Datasets/Rolls/Roll.yaml'
```

Figure 4. Dataset preparation: YAML conversion and training initiation in YOLO. Source: Developed by author based on L. Hosudarskiy (personal communication, December 1, 2024)

**Step 3. Feature Engineering:** synthetic image generation. To strengthen the model's ability to generalize, synthetic images of products were generated, introducing variations in appearance and environmental factors. This approach augmented the dataset, making the model more robust and effective (Appendix F).

**Step 4. Model deployment.** To check the quality of the model, the K-Fold Cross-Validation method was used. The basic formula for this method has been utilized and computed in YOLO (DataCamp. 2024; GeeksforGeeks, 2024):

$$VS = \frac{1}{K} \sum_{k=1}^{K} Score_k \tag{1}$$

where *VS* is the validation score, *K* is the number of dataset partitions, and $Score_k$ is the metric for the *k*-th partition. The summation aggregates the scores across all folds, while $\frac{1}{k}$ averages these scores to provide the final validation score.

Figure 6 illustrates the process of dividing the dataset into five equal parts for training and testing machine learning models. Each fold acts as a test set once, while the remaining folds are used for training. This iterative approach ensures that the model is evaluated across different data subsets, providing a more comprehensive assessment of its performance.

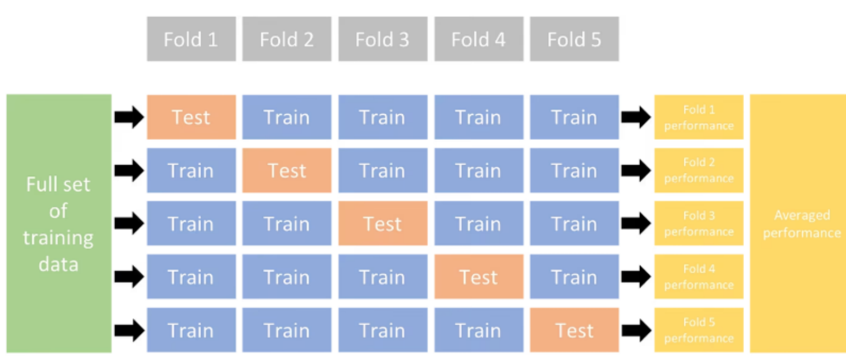



Figure 6. Dataset split guide (K-Fold cross-validation).
Source: Data reprinted from (Ultralytics, 2024)

This approach based on Formula 1 ensures that the model's performance is assessed across all parts of the dataset, offering a more reliable and unbiased evaluation by reducing the risk of overfitting or variability caused by a single train-test split. In our implementation, K=5, meaning the dataset was divided into 5 equal parts. Each part serves as a validation set once while the remaining parts are used for training, and the final performance metric is the average of all five iterations. (Figure 5).

```
[ ] folds_df.to_csv(save_path / "kfold_datasplit.csv")
    fold_lbl_distrb.to_csv(save_path / "kfold_label_distribution.csv")
    labels_df.to_csv(save_path / "kfold_labels_df.csv")
```

Figure 5. K-Fold data split and label distribution for training assessment.
Source: Developed by author based on L. Hosudarskiy (personal communication, December 1, 2024)

The model performance was evaluated using the mAP50 (Mean Average Precision) metric. (Kili Technology, 2024). This metric measures the average recognition accuracy based on correct matches between predicted and real objects. The formula has been utilized and computed in YOLO:

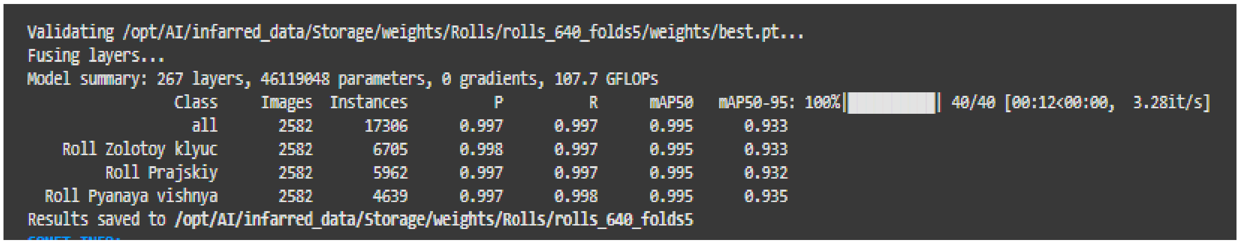
$$mAP = \frac{1}{N} \sum_{k=1}^{k-n} AP_k \qquad (2)$$

where $mAP$ stands for mean Average Precision, a metric used to evaluate the overall performance of a model across multiple classes. $n$ represents the total number of classes being evaluated; $AP_k$ $r$efers to the Average Precision for the $k$-th class, which is calculated as the area under the Precision-Recall curve for that specific class; the summation adds the AP values of all classes, and $\frac{1}{N}$ averages this sum by dividing it by the total number of classes.

The Formula 2 provides an aggregate measure of the model's ability to detect and classify objects across all classes.

**Step 5. Model evaluation and validation.** This step involves validating the trained YOLO model to assess its performance on unseen data and results are presented in Figure 7.

The provided metrics summarize the evaluation include number of layers and parameters and class performance metrics.



```
Validating /opt/AI/infarred_data/Storage/weights/Rolls/rolls_640_folds5/weights/best.pt...
Fusing layers...
Model summary: 267 layers, 46119048 parameters, 0 gradients, 107.7 GFLOPs
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100%|██████████| 40/40 [00:12<00:00,  3.28it/s]
                   all       2582      17306      0.997      0.997      0.995      0.933
     Roll Zolotoy klyuc       2582       6705      0.998      0.997      0.995      0.933
          Roll Prajskiy       2582       5962      0.997      0.997      0.995      0.932
   Roll Pyanaya vishnya       2582       4639      0.997      0.998      0.995      0.935
Results saved to /opt/AI/infarred_data/Storage/weights/Rolls/rolls_640_folds5
```

Figure 7. Validation results of YOLO model for product classification.

Source: Developed by author based on L. Hosudarskiy a

(personal communication, December 1, 2024)

The YOLO model comprises 267 layers and 46,119,048 parameters, indicating a complex architecture capable of handling detailed object detection tasks. Also, class performance metrics:

- **Precision (P)** reflects the model's accuracy in identifying correct instances. High values (e.g., 0.997 for "Roll Prajsky") confirm reliable predictions.
- **Recall (R)** measures the proportion of actual positive cases identified by the model. High recall values indicate comprehensive detection.
- **mAP50** is the Mean Average Precision at IoU=50. A near-perfect score of 0.997 shows excellent performance for all classes.
- **mAP50-95** extends the precision-recall evaluation over multiple IoU thresholds. A result of 0.933 demonstrates robustness across varied object overlaps.

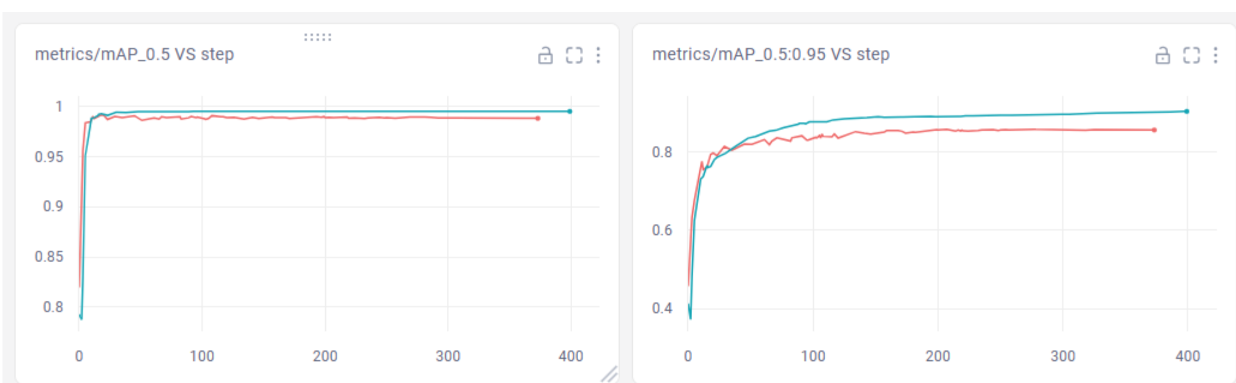



Figure 8. YOLO model training: mAP metrics over training steps.

Source: Developed by author based on L. Hosudarskiy (personal communication, December 1, 2024)

Figure 8 visualizes the performance metrics of the YOLO model during training, in particular:

- **Left Graph (mAP@0.5 vs. Steps)** displays the progression of Mean Average Precision (mAP) at IoU=0.5 over training steps. The curve shows a quick rise and stabilization near 1.0, indicating high accuracy in detecting objects after sufficient training iterations.
- **Right Graph (mAP@0.5:0.95 vs. Steps)** tracks the mAP across IoU thresholds ranging from 0.5 to 0.95. The gradual rise and eventual plateau demonstrate the model's improved robustness over diverse object overlaps as training progresses.

Both graphs in Figure 8 highlight effective convergence, validating the training process and the model's ability to generalize well on unseen data.

**Step 6. Deployment.** A merchandiser takes photos of product shelves during a visit to a retail outlet through a corporate CRM application. The photos are transferred to an FTP server, and the CRM system groups them into photo reports and sends them to the RabbitMQ queue in JSON format (Appendix E). Rabbit transfers the data to the YOLO web server for recognition, after which the ERP system integrates the results, evaluates merchandisers' KPIs, and generates management reporting.

Hence, the described process in 6 steps (developing and implemented ML solutions to automate the verification of store visit results) allowed the company to achieved the results to be described and analyzed in the following sections of the project.

## 2.2. Evaluating the ML-driven solution's technical performance and business impact on the optimization management at Confectionery Corporation "Roshen"

The implementation of ML solutions at Roshen has become an important stage in optimizing business processes aimed at increasing data accuracy, automating routine operations, and increasing economic efficiency. This section examines the key results of the implementation, including reducing operating costs, increasing sales, and eliminating the risks of data manipulation.

In order to define this success, we conducted overall evaluation the ML solution's technical performance and their managerial (expressed in business metrics) impact at Roshen. The technical metrics are: precision, recall and F1 Score (AWS Documentation, 2024; Microsoft Learn, 2024; Shung, 2024). Table 2 represents outcomes of evaluated the ML model’s technical performance.

Table 2. Technical evaluation of ML solution implemented at Roshen

| Technical metrics | Value | Description | Results |
|---|---|---|---|
| Precision | 0.997 | Indicates the accuracy of correct predictions. A high value indicates minimal false positives when checking for compliance with the calculation standards. | High accuracy of product detection on shelves is ensured, and the number of false positives is reduced. |
| Recall | 0.996 | Measures the model's ability to find all relevant positive cases, for example, identifying all cases of product layout inconsistency. | Almost all cases of non-compliance with standards were identified, which contributes to effective control of the calculation. |
| F1 Score | 0.996 | Harmonic mean between Precision and Recall, showing balanced model performance. Used to evaluate system performance in conditions where both missed cases and false alarms are important. | The optimal ratio of accuracy and completeness is provided to improve management decisions. |

Source: Developed by author based on L. Hosudarskiy (personal communication, December 1, 2024)

The Table 2 outcomes represent that the ML solution demonstrated good technical performance, achieving high levels of accuracy, reliability, and efficiency. Metrics such as Precision, Recall and F1Score indicate that the model effectively balances accuracy and completeness, providing robust detection and classification capabilities.

Appendix A shows the results of product recognition in an ERP system, while Appendix B highlights the detection of deviations from product quantity standards. Additionally, Appendix C contains metrics for analyzing shelf utilization.

In the context of automating product display monitoring, it is worth noting a significant expansion of the coverage of points of sale. Before the implementation of ML solutions, shelf monitoring was carried out manually and covered only 300 retail outlets per month. Thanks to the automation of the data processing process, the coverage increased to 2,000 points, which is a 6.67-fold increase. This provided more complete control over compliance with display standards, increased the geographical coverage of monitoring and improved the quality of product presentation in retail outlets (Appendix A).

The results of the implementation demonstrate a significant positive impact on key business performance indicators and personnel management. In particular, this implementation significantly optimized the work of supervisors. Previously, their activities included checking photo reports, which took an average of 2-3 hours per day, geolocation verification (1-2 hours per day) and drawing up reports on violations (1 hour per day) (Appendix B). After automation, the time for checking photo reports was reduced to 30 minutes per day, geolocation verification is automatic, and report generation is automated by 90%.

Significant progress has been made in increasing the accuracy of analysis. Algorithms, including YOLO, provide accuracy of product recognition on shelves up to 98% (Appendix C). This is achieved through the use of advanced computer vision technologies, continuous training and improvement of models, regular updating of product databases and the use of methods for validating results. Optimization of the data update frequency has also undergone significant changes - if previously reports were generated once a week, now the information is updated daily, which led to a reduction in the total data processing time by 85%.

The business metrics have been selected based on a conducted literature review (Lee, I., & Shin, Y. J.,2020; Cao, L., & Li, W. 2023) and approved by external and internal experts (L. Hosudarskiy, O. Petrovskiy, V. Ivanov). The business metrics are associated with measurements of cost, revenue, productivity improvements and personal engagement, all these lead to quantitative evaluation of the decision making process at the company. Table 3 represents a comprehensive measurement framework developed by the author using the baseline comparison technique.

Table 3. Quantified business impact of ML solution on Confectionery Corporation "Roshen"

| Business Metrics | Indicators | Before ML implementation (average for 2022-2023) | After ML implementation | Change, % |
|---|---|---|---|---|
| Cost Savings and Revenue Gains | Sales revenue | confidential | confidential | +4.02% |
| | Profit margin | 20% | 23.5% | +3.5% |
| | Operating expenses | 100% | 80% | -20% |
| | Printing/document processing costs | 100% | 10% | -90% |
| Productivity Improvements | Time saved by supervisors | 2-3 hours/day | 20 minutes/day | -80% |
| | Overall team efficiency | 100% | 112% | +12% |
| | Quality of photo reports | 85% compliant | 99% compliant | +14% |
| Engagement | Employee turnover | 27.75% | 12.75% | -15% |
| Investment effectiveness | Return on Investment (ROI), % | - | 542.46% | |

Source: Developed by author based on V. Ivanov (personal communication, December 1, 2024)

Financial optimization indicators demonstrate a total reduction in operating expenses in the direction of merchandising by 20%, a reduction in transportation costs by 30%, and savings on administrative costs of about 20% . The system automatically compares GPS data with the location of the retail outlet, which completely eliminates the possibility of changing coordinates and ensures 100% reliability of visiting points (V. Ivanov, personal communication, December 1, 2024).

The quality of photo reports has also improved significantly - the share of photos that meet the display standards has increased to 99%, and the time for checking photo reports has decreased from 2 hours per merchandiser to 10 minutes. Automatic detection of violations of display standards and an instant notification system for critical deviations have been implemented (V. Ivanov, personal communication, December 1, 2024).

Improved control over compliance with contract terms led to a 5% increase in sales and improved relations with partners. The economic effect was manifested in a 4.02% increase in revenue compared to the previous period, an increase in margin by 3.5%, a reduction in losses from suboptimal calculations by 4.2%, and an increase in the effectiveness of promotional campaigns by 12%. The personnel motivation system has undergone a significant transformation. If earlier the performance evaluation was subjective, with irregular feedback and the absence of clear evaluation criteria, then after the implementation of ML solutions, an objective evaluation based on KPIs, regular automated feedback, and a transparent bonus system appeared. This led to an 18% increase in average job satisfaction and a 15% decrease in employee turnover. Moreover, positive ROI indicates that the ML solutions should be scaled and implemented (Table 3).

An automated KPI assessment system allows to set individual performance indicators, conduct daily performance monitoring, and form personalized development plans. The overall team efficiency increased by 12%, the response time to deviations decreased by 70%, labor productivity increased by 25%, and the quality of calculations improved by 15% . Significant progress was made in optimizing personnel training. The training time for a new employee was reduced from 2 weeks to 5 days due to the standardization of training processes and the implementation of an automated knowledge assessment system. The contract compliance rate increased to 97%, which helped minimize penalties and preserve the company's reputation. Digitalization of document flow led to a 90% reduction in printing and document processing costs (V. Ivanov, personal communication, December 1, 2024).

The results of implementing ML solutions at Roshen Confectionery Corporation confirm that automation and optimization of processes significantly increased the efficiency of personnel management, minimized costs and improve interaction with partners, hence facilitated the decision making process. The achieved indicators indicate the long-term prospects for the development of ML technologies as a key tool in modern business.

# CHAPTER 3. IDENTIFICATION OF IMPROVEMENTS AND LIMITATIONS OF THE STUDY

## 3.1 Suggesting improvements for ML-driven decisions in retail management

Based on the conducted study of the implementation of ML solutions in the Roshen and the analysis of world experience in using machine learning in retail, a number of significant improvements can be proposed to increase the efficiency of management decision-making in the industry.

Expanding the functionality of the image recognition system is one of the priority areas for improvement. The current YOLO system demonstrates high accuracy in recognizing products on shelves, but there is potential for implementing additional functions. In particular, it is recommended to integrate the ability to analyze the location of competitive products, which will allow assessing the competitive environment and promptly responding to changes in the market situation. It is also advisable to implement the function of automatically determining the optimal location of products based on historical sales data and customer behavior.

Improving the demand forecasting system is critically important for optimizing inventory management and production planning. It is proposed to develop a comprehensive model that will take into account not only historical sales data, but also external factors such as seasonality, weather conditions, economic indicators and marketing activities. The use of deep learning methods and neural networks will increase the accuracy of forecasts and reduce the cost of storing excess inventory.

Integration of a system of personalized recommendations for sales representatives can significantly increase the efficiency of their work. Based on the analysis of historical sales data, location features and characteristics of retail outlets, the system can generate individual recommendations on the optimal assortment, delivery volumes and promotional activities for each point of sale.

Automation of the pricing process is a promising direction for improving ML solutions. It is proposed to implement a dynamic pricing system that will take into account a variety of factors: current demand, competitive environment, seasonality, product shelf life and other relevant parameters. This will maximize profits and minimize losses from markdowns.

The development of predictive analytics for assessing personnel efficiency is an important direction for improvement. It is recommended to create a system that, based on historical data on employee productivity, their qualifications and experience, will be able to predict potential problems and determine the optimal ways of staff development. This will help improve the process of planning training and advanced training of employees.

The implementation of computer vision technologies to analyze customer behavior in retail outlets can provide valuable information for optimizing the display of goods and planning retail space. The system can analyze customer movement trajectories, time spent near different categories of goods and the frequency of interaction with products, which will allow making more informed decisions about merchandising.

The development of an automated product quality control system is an important aspect of improving ML solutions. It is proposed to implement algorithms that, based on photo analysis, will be able to detect packaging defects, violations of storage conditions and other deviations from quality standards. This will increase the level of quality control and reduce the number of complaints from consumers.

Optimization of logistics processes using ML can significantly increase distribution efficiency. It is recommended to implement a system that will take into account data on traffic, weather conditions, warehouse occupancy and other factors to optimize delivery routes and plan vehicle loading. This will reduce logistics costs and improve the timeliness of deliveries.

The development of a customer experience management system is a promising area of improvement. It is proposed to create a comprehensive system for analyzing consumer feedback, which will include natural language processing to analyze comments on social networks, reviews on websites and survey results. This will allow for a better understanding of consumer needs and a prompt response to their requests.

The implementation of an early risk detection system can significantly improve the process of making management decisions. It is recommended to develop a model that, based on the analysis of various indicators (financial, operational, market), will be able to predict potential problems and suggest preventive measures to avoid them.

Automation of the reporting process is an important area of improvement. It is proposed to create a system that will automatically generate analytical reports of various levels of detail with visualization of key indicators and recommendations for process optimization. This will reduce the time for preparing reports and improve the quality of analytical information.

The development of a knowledge management system is critical to ensuring the effective use of ML solutions. It is recommended to create a centralized platform for collecting, systematizing and disseminating knowledge about the best practices of using ML technologies in retail management. This will help to speed up the process of training personnel and increase the efficiency of implementing new solutions.

Improving the data integration system from various sources is necessary to improve the quality of analytics. It is proposed to implement a single platform for collecting and processing data from various systems (ERP, CRM, POS terminals, websites, mobile applications), which will allow obtaining a more complete picture of business processes and making more informed decisions.

The implementation of Big Data processing technologies is an important direction in the development of ML solutions. It is recommended to use modern data storage and processing technologies to ensure the ability to analyze large volumes of information in real time. This will increase the speed and quality of management decision-making.

An important direction for the development of ML solutions is the implementation of big data processing technologies. It is recommended to use modern data storage and processing technologies to provide the ability to analyze large volumes of information in real time. This can be achieved using cloud platforms such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP), which offer scalable infrastructure to manage data from thousands of sensors and devices at optimized costs (AWS, 2024; Microsoft Azure, 2024). These platforms provide scalable storage, built-in machine learning services, pay-as-you-go solutions, and automatic backups, which can significantly reduce operational costs. The use of such solutions will provide budgeting transparency and contribute to the speed and quality of management decision-making while maintaining cost efficiency.

Improving the user interface of ML solutions is important to ensure their effective use. It is recommended to develop an intuitive interface with the ability to customize it to the needs of different categories of users, which will reduce the time for staff training and increase work productivity. Monitoring and evaluating the effectiveness of implemented improvements is a necessary element of the development of ML solutions. It is recommended regularly (monthly or quarterly) assess the impact of each improvement on key business performance indicators and analyze the results obtained to determine priority areas for further development as per Table 3.

The proposed improvements to ML solutions in retail management are aimed at increasing the efficiency of business processes, improving the quality of customer service, and optimizing costs. Their phased implementation will allow creating a comprehensive system of support for management decision-making that will meet modern market requirements and provide the enterprise with competitive advantages.

### 3.2 Identification of limitations of ML-driven solutions on managerial decision-making process in the retail industry

Based on the conducted study of the implementation of ML solutions in the Roshen Confectionery Corporation and the analysis of the world experience of using machine learning in retail, a number of significant limitations and challenges can be identified that affect the effectiveness of management decision-making.

Technological limitations constitute the first category of challenges in the implementation of ML solutions. The quality and reliability of image recognition largely depends on the quality of input data - photographs taken by merchandisers. Poor lighting, blurry images or partial overlap of goods can lead to recognition errors. In addition, the YOLO system, which is used to analyze the display of goods, requires constant updating and retraining when new products appear or the packaging of existing ones changes, which creates an additional load on the IT infrastructure.

The problem of data quality and availability is a critical limitation for the effective functioning of ML systems. Accurate demand forecasting and inventory optimization require large amounts of historical data, which are not always available, especially for new products or retail outlets. In addition, data can be incomplete, contain errors, or be unstructured, making it difficult to process and analyze. This problem is especially acute when trying to integrate data from different sources – ERP systems, POS terminals, warehouse accounting systems, etc.

Human factor limitations constitute a significant part of the challenges. There is resistance from staff to the implementation of new technologies, especially among older workers. Many employees perceive ML systems as a threat to their employment or do not trust automated solutions. There is also a problem of insufficient technical literacy of staff, which makes it difficult to effectively use ML tools and interpret their results.

Financial constraints are a significant factor affecting the implementation of ML solutions. The initial investment in the development and implementation of ML systems can be significant, including costs for equipment, software, staff training, and infrastructure support. In addition, ongoing costs for maintaining and updating systems can be a significant part of the operating budget, which is especially critical for small and medium-sized enterprises.

Legal and ethical constraints also pose certain challenges. The use of ML systems to collect and analyze data on consumer behavior must comply with the requirements of personal data protection legislation. In addition, there are ethical issues regarding the transparency of decision-making algorithms and the possibility of their bias, especially in the context of personnel management and assessing its performance.

Limitations related to the scalability of solutions are manifested when trying to expand the system to new regions or product categories. ML models trained on data from one region or product category may show worse results when applied in other conditions. In addition, an increase in the number of retail outlets and data volume can lead to an increase in the load on the system and a decrease in the speed of information processing.

Integration constraints arise when ML systems need to interact with the existing IT infrastructure of the enterprise. There are often problems with compatibility with legacy systems, difficulties in organizing data exchange between different platforms and ensuring the smooth operation of integrated solutions. This can lead to delays in data processing and decision-making.

Limitations in forecasting accuracy constitute a separate category of challenges. Despite the use of sophisticated algorithms, ML models cannot take into account all possible factors affecting demand and sales. It is especially difficult to predict demand for new products, the market's reaction to price changes, or the impact of unpredictable events (for example, pandemics or economic crises).

Limitations in system flexibility appear when it is necessary to respond quickly to changes in the market situation. ML models trained on historical data may not have time to adapt to sharp changes in consumer behavior or market conditions. In addition, making changes to the system's operating logic often requires significant time and resource costs.

Cybersecurity issues pose a serious challenge for ML systems. Storing and processing large amounts of data makes systems attractive targets for cybercriminals. In addition, ML algorithms themselves can be vulnerable to attacks aimed at manipulating the results of their work.

Limitations in the interpretation of results are a significant challenge for management decision-making. The complexity of machine learning algorithms often makes them a “black box” where the decision-making process is not transparent to users. This can lead to distrust in the system and difficulties in justifying the decisions made.

Technical infrastructure limitations can create problems in the operation of ML systems. Insufficient network bandwidth, limitations in computing power, or problems with Internet access can lead to delays in data processing and decision-making.

Limitations in knowledge management are manifested in the difficulty of preserving and transferring experience in using ML systems. When key employees who understand the principles of the system's operation are dismissed, problems may arise with its further development and support. In addition, there is a problem of documenting knowledge and creating effective training materials.

Cultural limitations can affect the effectiveness of implementing ML solutions. The traditional decision-making culture, based on the intuition and experience of managers, may conflict with an approach based on data and algorithms. This can lead to resistance to change and inefficient use of the system's capabilities.

Coordination problems between different divisions of the enterprise can complicate the implementation and use of ML solutions. Different departments may have different priorities and requirements for the system, which complicates the process of its development and implementation. In addition, there may be problems with the distribution of responsibility for different aspects of the system's operation.

Limitations in the capabilities of the support system can create problems when technical failures occur or changes need to be made. This is especially critical for companies that do not have their own staff of technical specialists and depend on external service providers.

Problems with assessing the effectiveness of ML solutions can complicate the decision-making process for further system development. It is difficult to determine the direct impact of ML implementation on the financial performance of the company, especially in the short term. In addition, there are difficulties in determining the optimal balance between the costs of system development and the benefits received.

Awareness and understanding of these limitations is critical for the successful implementation and use of ML solutions in retail and allow decision maker body of a company to:

- better plan the process of system implementation and development;
- develop strategies to overcome or minimize the impact of limitations;
- set realistic expectations about the capabilities of the system;
- more effectively allocate resources to the development of different aspects of the system;
- ensure a more balanced approach to making management decisions.

The analysis of improvements and limitations in the study was conducted and outcomes shown in APPENDIX G using the Technology Acceptance Model (TAM), providing a comprehensive evaluation of the adoption and effectiveness of ML solutions at Confectionery Corporation “Roshen” (Newcastle University, 2025).

It is important to note that many of these limitations are dynamic, hence can be overcome or minimized through the implementation of appropriate organizational and technical solutions. The key factor for success is a systematic approach to implementing ML solutions, which takes into account all aspects of the enterprise's activities and ensures the gradual development of the system, taking into account existing limitations and opportunities.

## CONCLUSIONS AND AREAS FOR FUTURE RESEARCH

The increasing complexity of retail operations, combined with the exponential growth of data, makes machine learning-based solutions not just useful, but essential for modern retail management. The ability to analyze large volumes of data and respond quickly to changes significantly increases the competitiveness of companies and encourage them to implement ML tools. However it requires deep study and analysis.

The conducted study of the role of machine learning as a tool in improving management decisions in the retail industry, in particular on the example of the implementation of ML solutions in the Confectionery Corporation "Roshen", made it possible to formulate a number of important conclusions and identify promising areas for further research.

Conducted study identified that retail industry (globally as well as domestically) is undergoing a fundamental transformation under the influence of machine learning technologies. Traditional approaches to data processing and management decision-making, which were based on manual methods and situational sampling, no longer meet the modern requirements of the industry. The growing complexity of retail operations, the need to process large volumes of data and the need to make informed decisions in real time necessitate the implementation of ML solutions.

Analysis of world retail experience has shown that the use of machine learning has a wide range of applications (optimizing supply chains, forecasting demand, personalization of marketing offers, automating quality control processes, etc.). ML solutions allow companies to significantly increase the efficiency of their operations, improve the quality of customer service and enhance the decision making process.

The practical implementation of ML solutions at Roshen has demonstrated significant positive results in several key areas. The implementation of an automated product display monitoring system has increased the coverage of points of sale from 300 to 2,000 per month, while the accuracy of product recognition has reached 98%, and the total data processing time has been reduced by 85%. Operating costs have undergone significant optimization: merchandising costs have decreased by 20%, transportation costs have decreased by 30%, and savings on administrative costs have amounted to about 20%.

A significant achievement has been the improvement of data quality and process transparency. The implementation of ML solutions allowed to completely eliminate geolocation manipulation, increase the share of photos that meet the standards to 99%, and reduce the time for checking photo reports from 2-3 hours to 20 minutes per merchandiser. This directly affected the company's financial performance: the share of sales increased by 5%, revenue increased by 4.02%, margin increased by 3.5%, and the effectiveness of promotions increased by 12%.

Particular attention should be paid to the results of optimizing human resources management. The overall efficiency of the team increased by 12%, the response time to deviations decreased by 70%, labor productivity increased by 25%, and staff turnover decreased by 15%. These indicators indicate a comprehensive positive impact of ML solutions not only on operational efficiency, but also on organizational culture and staff satisfaction.

Based on the study, promising areas for improving ML solutions were identified. In particular, it is necessary to expand the functionality of image recognition systems, including the implementation of competitive environment analysis and automation of determining the optimal location of products. An important area is the improvement of forecasting systems through the development of complex demand forecasting models and the integration of external influencing factors. The development of decision support systems is also relevant, including the creation of personalized recommendation systems and automation of the pricing process.

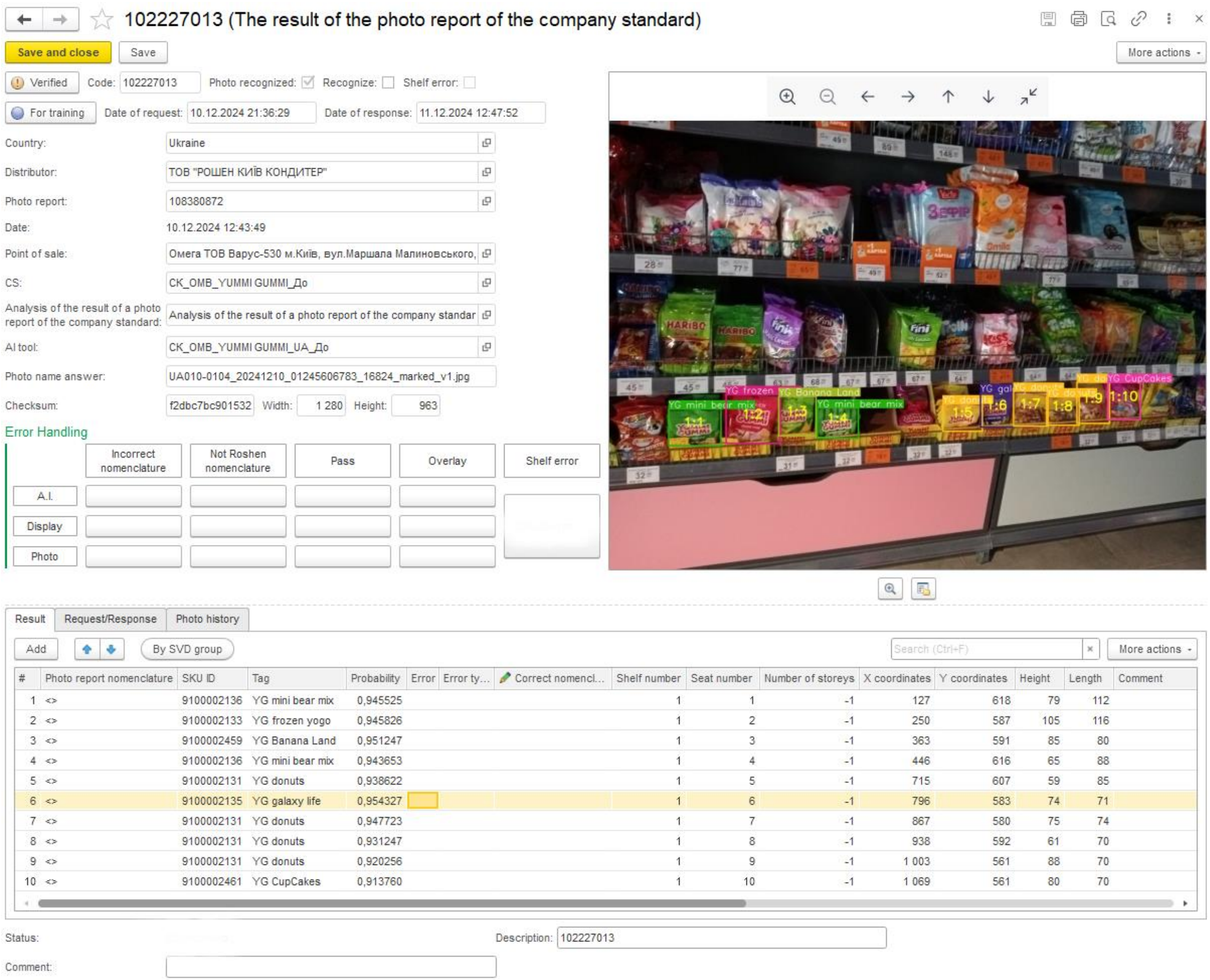
Hence, based on conducted study, were formulated practical recommendations for managerial decision-makers in retail industry. Since the successful implementation of ML solutions requires careful preparation (including a detailed audit of existing processes and an assessment of the readiness of infrastructure and personnel), it is important to ensure proper organization of the implementation process by creating cross-functional teams and ensuring proper training of personnel. Also, in order to ensure sustainable development, it is necessary to create an effective knowledge management system and develop a data culture in organizations.

The study identified a number of limitations and problems that accompany the implementation of solutions based on ML machine learning. Of the technological limitations, the most significant are the dependence on the quality of input data, the need for constant updating and retraining of models, as well as problems with the scalability of solutions. Organizational problems include staff resistance to the implementation of new technologies, insufficient technical literacy of employees, difficulties in integrating into existing business processes. Financial limitations consist in the need for significant initial investments and a certain high cost of modifying the system for other business processes.

The study opened a number of promising areas for additional scientific research. Of particular interest is the study of the impact of ML-based solutions on the long-term activities of the enterprise, including the assessment of the impact on financial indicators and the competitiveness of the enterprise. An important area of research is the possibility of integrating new technologies, such as generative AI and computer vision technologies, for example, for automated quality control of packaging. Research into the social aspects of ML implementation remains relevant, especially in the context of the impact on employment and job automation.

The study confirms that the implementation of ML-based solutions is a crucial factor in increasing management efficiency in retail. For the future success, a key factor will be the ability to effectively combine the capabilities of ML technologies with human experience and intuition, creating synergies that will allow them to achieve new levels of efficiency and competitiveness in a dynamic market environment.

# APPENDIX A. THE RESULT OF PRODUCT RECOGNITION BY THE ML SOLUTION IS DISPLAYED IN THE ERP SYSTEM




| # | Photo report nomenclature | SKU ID | Tag | Probability | Error | Error ty... | Correct nomencl... | Shelf number | Seat number | Number of storeys | X coordinates | Y coordinates | Height | Length | Comment |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | <> | 9100002136 | YG mini bear mix | 0,945525 | | | | 1 | 1 | -1 | 127 | 618 | 79 | 112 | |
| 2 | <> | 9100002133 | YG frozen yogo | 0,945826 | | | | 1 | 2 | -1 | 250 | 587 | 105 | 116 | |
| 3 | <> | 9100002459 | YG Banana Land | 0,951247 | | | | 1 | 3 | -1 | 363 | 591 | 85 | 80 | |
| 4 | <> | 9100002136 | YG mini bear mix | 0,943653 | | | | 1 | 4 | -1 | 446 | 616 | 65 | 88 | |
| 5 | <> | 9100002131 | YG donuts | 0,938622 | | | | 1 | 5 | -1 | 715 | 607 | 59 | 85 | |
| 6 | <> | 9100002135 | YG galaxy life | 0,954327 | | | | 1 | 6 | -1 | 796 | 583 | 74 | 71 | |
| 7 | <> | 9100002131 | YG donuts | 0,947723 | | | | 1 | 7 | -1 | 867 | 580 | 75 | 74 | |
| 8 | <> | 9100002131 | YG donuts | 0,931247 | | | | 1 | 8 | -1 | 938 | 592 | 61 | 70 | |
| 9 | <> | 9100002131 | YG donuts | 0,920256 | | | | 1 | 9 | -1 | 1 003 | 561 | 88 | 70 | |
| 10 | <> | 9100002461 | YG CupCakes | 0,913760 | | | | 1 | 10 | -1 | 1 069 | 561 | 80 | 70 | |

Figure A1. Screenshot of product recognition results displayed in Roshen's ERP system.

Source: O. Petrovskiy (personal communication, December 1, 2024)

# APPENDIX B. DETECTION OF DEVIATIONS FROM PRODUCT QUANTITY STANDARDS

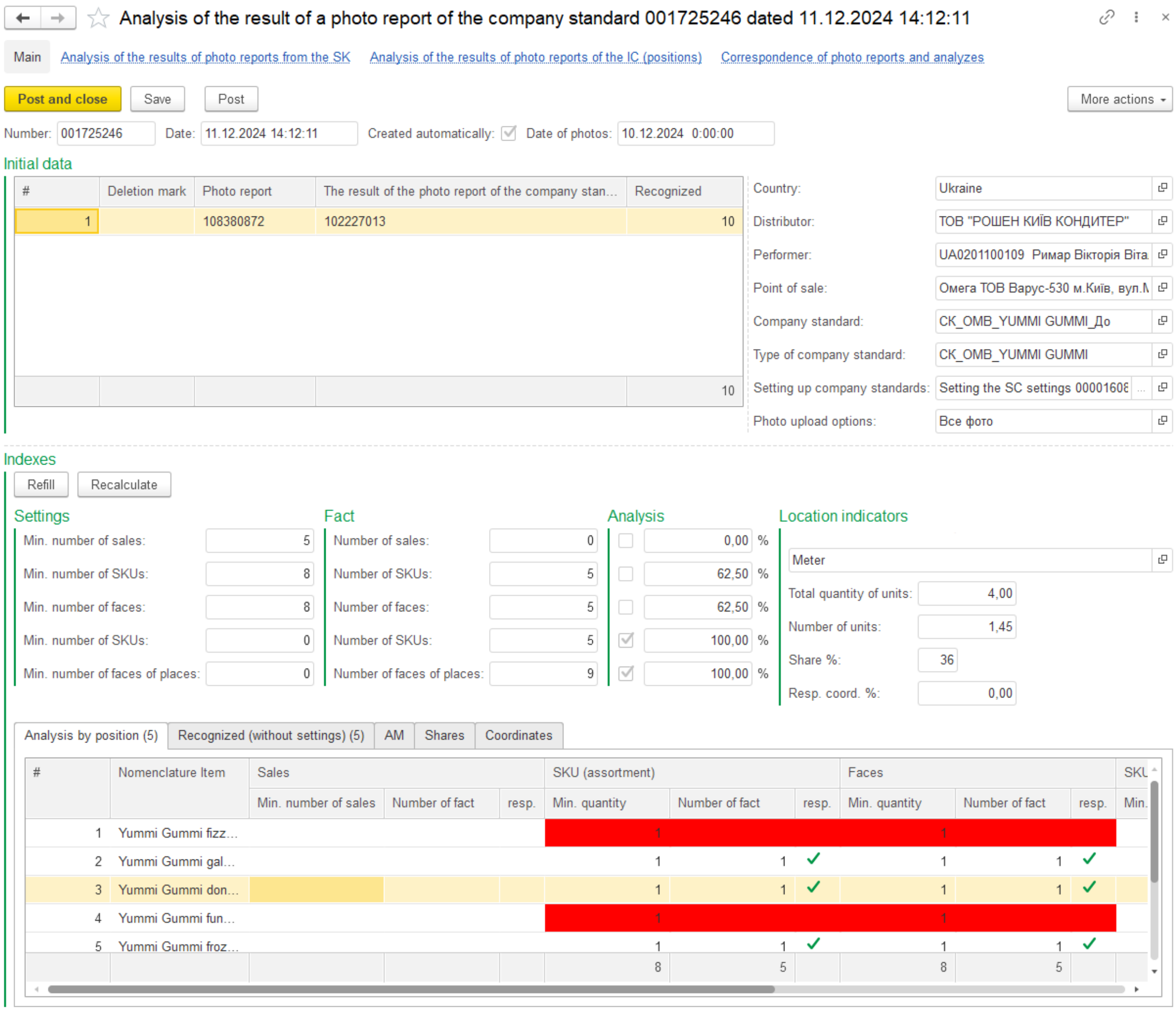



Figure B1. Screenshot of product quantity deviation detection interface in Roshen's ERP system.

Source: O. Petrovskiy (personal communication, December 1, 2024)

# APPENDIX C. DETERMINING THE PERCENTAGE OF SHELF SPACE FILLED WITH PRODUCTS AT THE POINT OF SALE

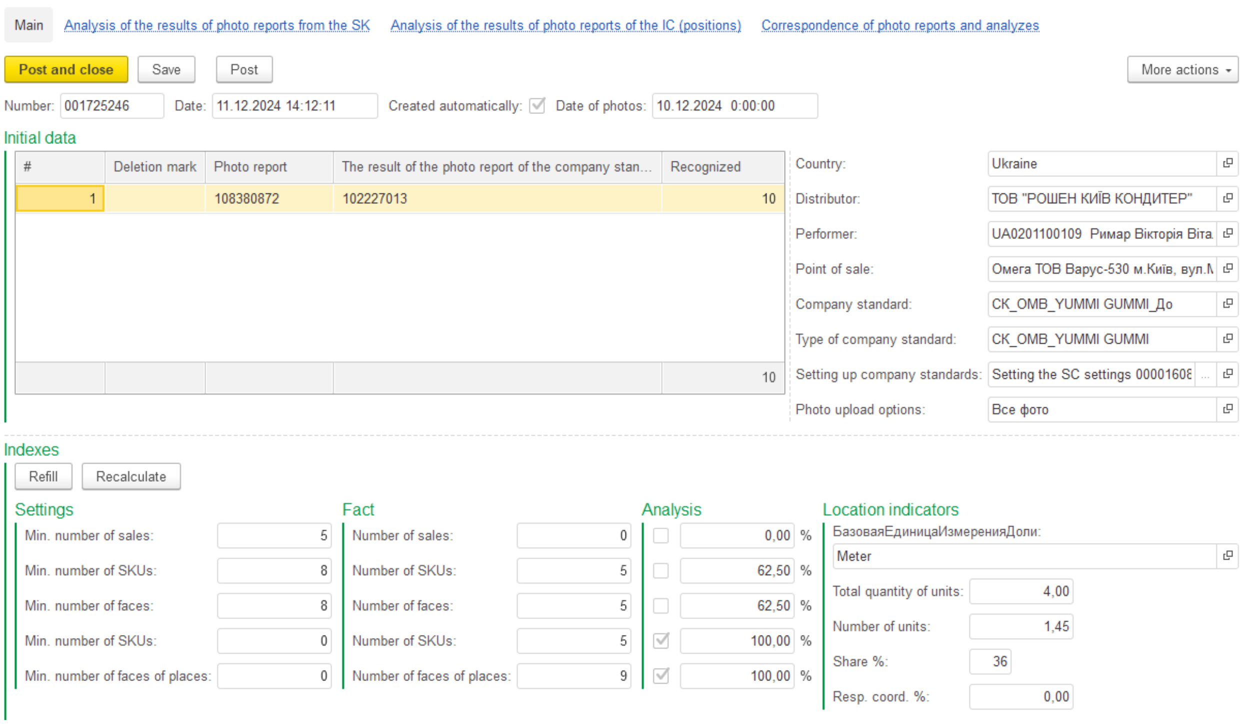



Figure C1. Screenshot of shelf space analysis metrics in Roshen's ERP system.

Source: O. Petrovskiy (personal communication, December 1, 2024)

## APPENDIX D. AN EXAMPLE OF PHOTO ANNOTATION FOR TRAINING AN ML MODEL

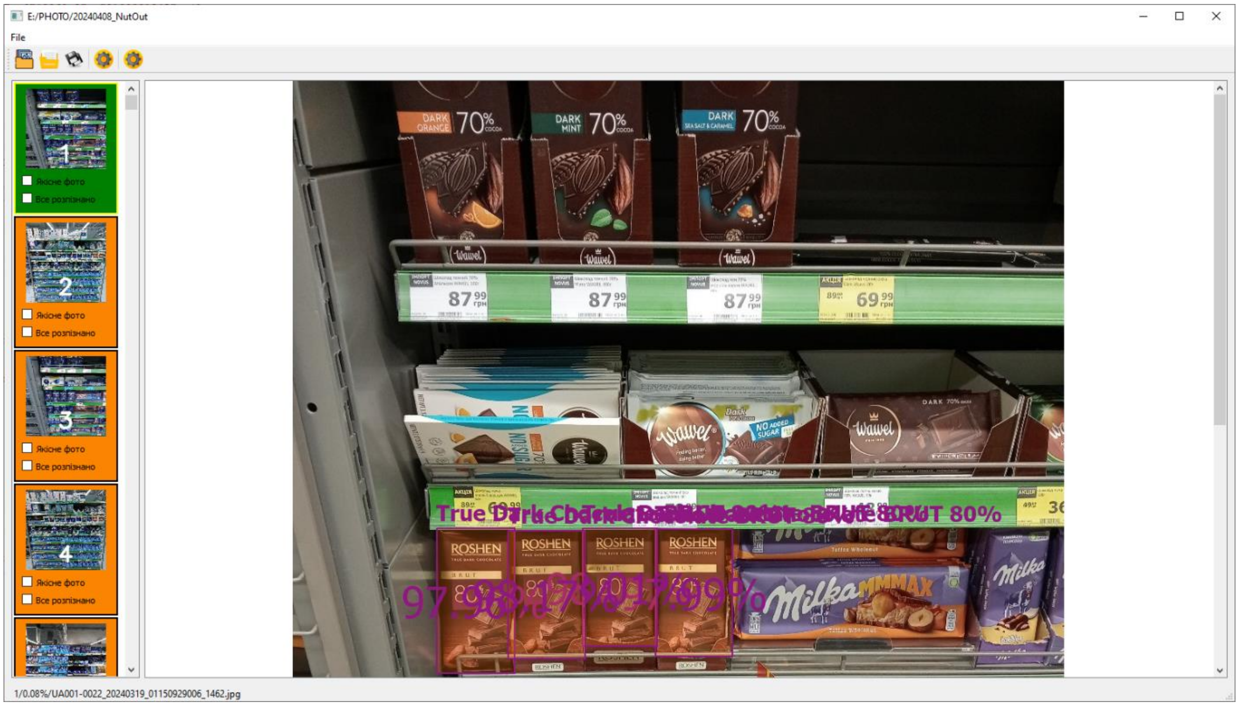
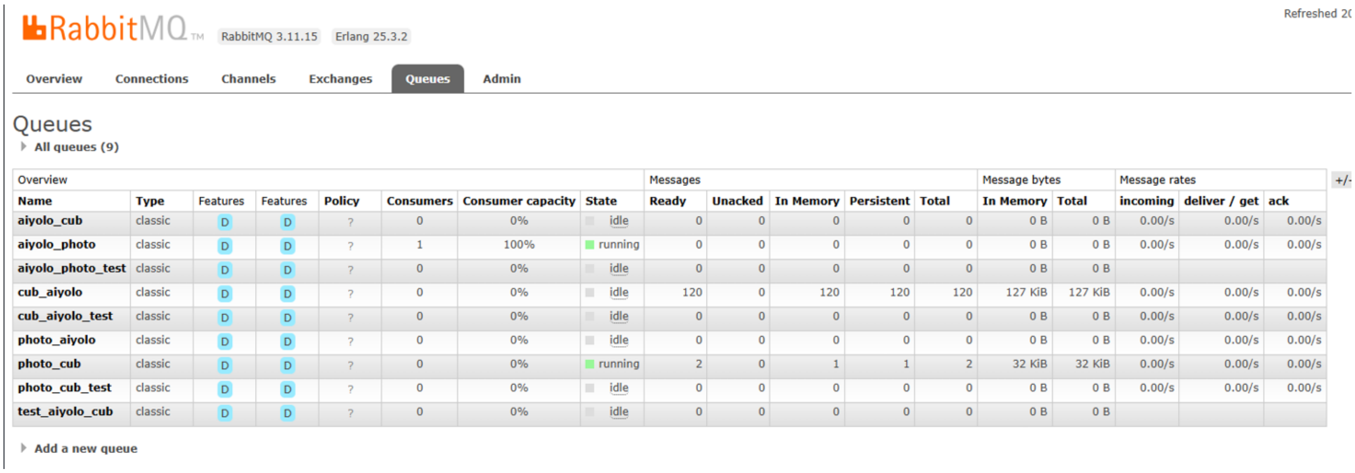



Figure D1. Screenshot of photo annotation interface used for ML model training.

Source: O. Petrovskiy (personal communication, December 1, 2024)

## APPENDIX E. PHOTO QUEUE PROCESSING




| Overview | | | | | | | | Messages | | | | | Message bytes | | Message rates | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Name | Type | Features | Features | Policy | Consumers | Consumer capacity | State | Ready | Unacked | In Memory | Persistent | Total | In Memory | Total | incoming | deliver / get | ack |
| aiyolo_cub | classic | D | D | ? | 0 | 0% | idle | 0 | 0 | 0 | 0 | 0 | 0 B | 0 B | 0.00/s | 0.00/s | 0.00/s |
| aiyolo_photo | classic | D | D | ? | 1 | 100% | running | 0 | 0 | 0 | 0 | 0 | 0 B | 0 B | 0.00/s | 0.00/s | 0.00/s |
| aiyolo_photo_test | classic | D | D | ? | 0 | 0% | idle | 0 | 0 | 0 | 0 | 0 | 0 B | 0 B | | | |
| cub_aiyolo | classic | D | D | ? | 0 | 0% | idle | 120 | 0 | 120 | 120 | 120 | 127 KiB | 127 KiB | 0.00/s | 0.00/s | 0.00/s |
| cub_aiyolo_test | classic | D | D | ? | 0 | 0% | idle | 0 | 0 | 0 | 0 | 0 | 0 B | 0 B | 0.00/s | 0.00/s | 0.00/s |
| photo_aiyolo | classic | D | D | ? | 0 | 0% | idle | 0 | 0 | 0 | 0 | 0 | 0 B | 0 B | 0.00/s | 0.00/s | 0.00/s |
| photo_cub | classic | D | D | ? | 0 | 0% | running | 2 | 0 | 1 | 1 | 2 | 32 KiB | 32 KiB | 0.00/s | 0.00/s | 0.00/s |
| photo_cub_test | classic | D | D | ? | 0 | 0% | idle | 0 | 0 | 0 | 0 | 0 | 0 B | 0 B | 0.00/s | 0.00/s | 0.00/s |
| test_aiyolo_cub | classic | D | D | ? | 0 | 0% | idle | 0 | 0 | 0 | 0 | 0 | 0 B | 0 B | | | |

Figure E1. Screenshot of RabbitMQ photo queue processing interface.

Source:O. Petrovskiy (personal communication, December 1, 2024)

## APPENDIX F. SYNTHETIC IMAGES OF PRODUCTS

Figure F1. Synthetic images of products for ML training

Source:O. Petrovskiy (personal communication, December 1, 2024)

# APPENDIX G. APPLICATION OF THE TECHNOLOGY ACCEPTANCE MODEL

| TAM Component | Description | Findings from the Project |
|---|---|---|
| Perceived Usefulness (PU) | The degree to which users believe that the ML solutions enhance their performance. | - Increased product recognition accuracy to 98%.<br>- Reduced operating costs by 20%.<br>- Improved decision-making speed by 70%. |
| Perceived Ease of Use (PEOU) | The degree to which users believe that using the ML solutions is free from effort. | - Automated processes reduced manual supervision time by 80%.<br>- Simplified user interfaces (e.g., ERP integration). |
| Attitudes Toward Use (ATU) | The users' positive or negative feelings about using ML solutions. | - Positive response from supervisors due to reduced workload.<br>- Some resistance observed among older staff and less tech-savvy employees. |
| Behavioral Intention to Use (BI) | The degree to which users intend to use ML solutions consistently in the future. | - High adoption potential due to tangible benefits.<br>- Plans to scale ML solutions to other areas like pricing automation and demand forecasting. |
| External Factors | Factors influencing TAM components, such as organizational support or resource availability. | - Strong organizational support for training and infrastructure.<br>- Initial resistance due to high costs and technical expertise requirements. |
| Actual System Use | How the system is used in real-world scenarios. | - Automated product display monitoring.<br>- Integration with ERP for real-time reporting.<br>- Enhanced KPI tracking and decision-making efficiency. |

Table G1. Application of the technology acceptance model (TAM) to the Machine Learning solutions at Confectionery Corporation "Roshen"

Source: Developed by author based on V. Ivanov (personal communication, December 1, 2024)

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