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LOWINFOOD

Multi-actor design of low-waste food value chains through the demonstration of innovative solutions to reduce food loss and waste

GA No. 101000439

D2.6: Report on demonstration - forecasting software at retail stores

WP2 - Type of deliverable: Report - Dissemination level: Public - Due date: 31st July 2024

HISTORY OF CHANGES after the first submission of the deliverable on 31/07/2025		
Date	***Change description***	***Reference to the EC request***
19/06/2025	*Section 1 amended*	*Following a remark of the reviewer, section 1 is improved by adding the working definition of food waste used in this demonstraion.*

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LOWINFOOD Consortium

N.	Full name of the organisation	Short name	Country
1	Università degli Studi della Tuscia	UNITUS	Italy
2	Alma Mater Studiorum Università di Bologna	UNIBO	Italy
3	Sveriges Lantbruksuniversitet	SLU	Sweden
4	FH Munster University of Applied Sciences	ISUN	Germany
5	The James Hutton Institute	JHI	United Kingdom
6	Universitaet Fuer Bodenkultur Wien	BOKU	Austria
7	Tampereen Korkeakoulusaatio SR	TAU	Finland
8	Charokopeio Panepistimio	HUA	Greece
9	Osterreichisches Okologieinstitut	AIE	Austria
10	Elhuyar Fundazioa	ELH	Spain
11	Matomatic AB	MATO	Sweden
12	Unverschwendet GmbH	UNV	Austria
13	Akademie Deutsches Baeckerhandwerknord GGmbH	ADB	Germany
14	Foresightee (terminated on 30/01/2023)	FOR	Belgium
15	Leroma GmbH	LER	Germany
16	Mitakus Analytics UG	MITA	Germany
17	Kitro SA	KITRO	Switzerland
18	Regione Emilia Romagna	RER	Italy
19	Pianeta Cospea srl	PICO	Italy
20	Cogzum Bulgaria OOD	COZ	Bulgaria
21	Uppsala Kommun	UPP	Sweden
22	Recuperiamo srl	REG	Italy
23	Antegon GmbH	FT	Germany
24	Confederazione Nazionale dell'Artigianato e della piccola e media impresa Associazione di Viterbo e Civitavecchia	CNA	Italy
25	Assemblee des Regions Europeennes Fruitieres Legumieres et Horticoles	ARE	France
26	L.V.L Anonymi Emporiki Toyristiki Kksenodoxeiaki Kataskevastiki Etaireia	BLU	Greece
27	Iridanos-Inabelos Anonymi Etaireiatouristikes Ksenodoxeiakes Kai Agrotikes Epixeiriseis	THA	Greece
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Summary

The deliverable 2.6 presents the work carried out to develop and demonstrate a forecasting software used to predict future sales of fruits and vegetables in supermarkets. The software uses neural networks and machine learning techniques to build a forecast based on store-specific historical data. The algorithm is trained to forecast sales of individual products of the fruits & vegetable department, on a daily/weekly basis. Such technology is expected to produce accurate forecasts that can help food category managers to prevent surplus ordering, thus reducing the amount of unsold products, and therefore the quantity of waste produced at the supermarket. The demonstration of the forecasting software has been conducted first as a pilot test in one supermarket and then as a full two-month demonstration in two Italian supermarkets. During the final demonstration phase, the model achieved a total absolute error of 32% in predicting sold quantities across all forecasted products in both stores, with the error calculated based on their monetary sales value. This represents a significant improvement over the baseline model currently used by the stores, which historically has had an absolute error of 55% during the same months for the same products. At the same time, the demonstration revealed a good interest of the food category managers – that is, the store staff in charge of ordering – towards the software and its capacity to support the ordering process with additional and reliable information.

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Introduction to the deliverable

LOWINFOOD is a project committed to co-design, together with actors of the food chain, low-waste value chains by supporting the demonstration of a portfolio of innovations in a set of value chains particularly concerned by food loss and waste (fruits & vegetables, bakery products and fish), as well as in at-home and out-of-home consumption. Each of these value chains corresponds to a single Work Package (WP) of the project.

The innovations are selected among promising solutions that have already been developed and tested by some partners of the consortium, with the aim to provide the necessary demonstration and upscale to allow market replication.

The LOWINFOOD consortium comprises 27 entities, located in 12 different countries, and ranging from universities and research institutes to start-ups, foundations, associations, and companies working in the food sector. During the 52 months of the project, the partners are committed to complete 30 tasks and to deliver 60 outputs (deliverables).

This deliverable (D2.6) is part of work package 2, which is dedicated to reducing waste in the supply chain of fruits and vegetables. More specifically, D2.6 is subsumed under task 2.4 (T2.4) which infers a technological innovation that will support supermarket staff to accurately predict future sales of fruits and vegetables so that over ordering that results in food waste can be avoided. The innovation itself is developed by the Swedish University of Agricultural Science utilising neural networks and machine learning techniques to forecast sales in the operational environment of supermarkets.

The deliverable presents the development and demonstration of the forecasting software. This was done in three steps, starting with the development of the software and training of the algorithm with data from three supermarkets, the functions and practical implementation was tested in a pilot demonstration in one supermarket, and the full demonstration was conducted for two months in two Italian supermarkets.

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1. Context of the demonstration

In Italy, food waste (FW) at retail stage consists of 4 million tonnes of fresh mass, that represents about 7% of the total food waste along the supply chain (Eurostat, 2023) and among the categories of food waste, the main fraction in mass is represented by fresh fruits and vegetables (FFV) at retail level, with a sales area higher than 3,500 m^2 (Cicatiello and Franco, 2020; Brancoli et al., 2017; Cicatiello et al., 2017; Lebersorger and Schneider, 2014). Even if the percentage of FW recorded at retail level is small if compared to the other phases of the FFV supply chain, they have a critical role, since their strategies have an impact both on customer preferences and on the suppliers (Cicatiello and Franco, 2020; Cicatiello et al., 2017; Gruber et al., 2016).

In Italy, it has been assessed that in one Italian store in 2015 the quantity of FFV waste detected over one year was 24,035 kg, corresponding to a value of 36,372 € (Cicatiello et al., 2017). In Sweden, a study covering three stores detected 68 tonnes of FFV wasted (Mattsson et al., 2018), while Eriksson et al. (2012) found that the rate of waste of FFV varied between 2.0% and 4.0% of the 9,605t supplied to six stores, and that reclamations (pre-store waste) contributed to 67% of the wasted mass (Eriksson et al., 2017).

Analyzing the causes of the waste, perishable nature of the products, followed by inadequate technological equipment to support their preservation are accounted (Tort et al., 2022). Retailers also face the challenge to predict the demand of products that has to be ordered and sold from one day to the following one. If inaccurate forecasting happens, they generate overproduction and excessive stocks (Magalhães et al., 2021), which is likely to become waste. Forecasting software is being introduced in the food retail sector to support the ordering process and avoid food waste (Dharmawardane et al., 2021), but it has never been tested in the Italian context, where retailers still use a naïve approach to predict the quantity of food items that will be sold in the next days.

In the context of the LOWINFOOD project, a forecasting software was tested and demonstrated at a sample of retail stores in Italy, belonging to one of the major retail chains of the country. The aim of the demonstration was to verify the extent to which these tools are able to improve the efficiency of supermarket operations and to reduce the quantity of FW produced. In the context of this demonstration, we focus on in-store retail FW, intended as any food item, either packed or unpacked, that is removed from shelves and treated as waste in the stores. Therefore, surplus food items that are sold at a discount, or donated to charities, are not accounted as waste in our assessment.

The focus of this demonstration is on FFV products. At these stores, food category managers are the persons in charge of ordering these products. Orders are usually AxB, meaning that the order placed in the morning is delivered on the following day. Food category managers place the order of FFV before 11 am. To decide the amount of each product to be ordered, the food category manager considers the quantity of that product that was sold on the day

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before and the remaining stock. Then, they check the sales recorded on the same week of the year before, during the upcoming weekday. For example, if it's the first Monday of May, and they are ordering for the next day – the first Tuesday of May – they check the sales recorded for that product, on the first Tuesday of May of the year before. Lastly, they adjust the order according to the weather conditions, because they greatly influence the consumption of several FFV products.

Despite the availability of validated technological tools to improve the sustainability of FFV supply chain, the key actors involved often lack the entrepreneurial skills necessary to understand the benefits of implementing innovations and engaging with other relevant stakeholders directly and or indirectly (Simms et al., 2020; Blasi and Cicatiello, 2019).

2. Introduction to the innovation

Forecasting software tools are essential in various industries for predicting future trends, events, and behaviors by analyzing historical data. The techniques vary widely in complexity, from simple methods that rely on basic mathematical calculations to advanced models that incorporate machine learning algorithms. In general, five type of overarching common forecasting techniques exist (Hyndman et al., 2018):

1. *Qualitative forecasting techniques* is often used when data is limited or when dealing with new products or technologies where little historical data exist. These methods rely heavily on expert opinions, market research, and comparative analysis.
2. *Time series analysis* is used extensively used in finance, sales forecasting, and inventory studies and often use moving averages, exponential smoothing or ARIMA (Autoregressive Integrated Moving Average) methods.
3. *Casual models* which assume that the variable to be forecasted is affected by other variables. These models are useful when changes in one or more independent variables can be used to predict changes in the dependent variable. Regression analysis or Econometric modelling are common methods applied for these types of forecasting techniques.
4. *Monte Carlo simulation and Scenario Analysis* which uses randomness to solve problems that might be deterministic in principle. Used for decision making under uncertainty whereas scenario analysis involved examining multiple scenarios to see how changes in one or more variable will affect the outcome.
5. *Machine Learning techniques* which use large datasets and advanced computing are becoming increasingly popular for making highly accurate predictions. Decision Trees, Neural networks and ensemble methods are examples of methods that can be deployed.

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Despite the versatility of forecasting techniques, there are inherent challenges such as: data quality issues where poor data quality can lead to inaccurate forecasts, Model overfitting where the model is too closely fit to a limited set of historical data, limiting the performance on newer data. External factors such as unpredictable events, such as economic downturns or pandemics can drastically affect the reliability of forecasts (Box et al., 2015).

The innovation developed within the LOWINFOOD project relies on Machine Learning techniques. Specifically, its core is based on Multi-Layer Perceptron (MLP) neural networks, chosen for their ability to capture complex and non-linear relationships in large datasets. For each product, several different MLP models were trained, with varying depths and widths. Deeper MLPs can capture more complex relationships but are more prone to overfitting.

The training was based on historical data of sales, promotions, prices recorded at three different stores of the retail company involved, during 6 years, from 2016 to 2021. For products sold every day in each store, there could be approximately 6,500 data points available. However, many products had considerably fewer data point, due to factors such as seasonality or being introduced after 2016.

After training multiple different models for each product, each model was evaluated on a portion of the historical data that the models had not seen during the training phase, in order to identify the best model under different circumstances. For example, a certain model may be better at predicting the effect of a sudden price change or promotion, while another model may be better suited for periods of stable prices.

For each day during the testing and demonstration periods, a model was chosen for each product, based on its performance under similar circumstances in the evaluation phase. The evaluation score was also included in the delivered forecasts, indicating the reliability of each predicted quantity.

The models use recent sales data for the product (between 3 and 10 days for different models), along with prices and ongoing promotions for those days. They also incorporate the price and promotions for the forecasted day. A set of temporal features are also used as input, including the day of the week, day of the month and month of the year, to help the model learn seasonal and weekly patterns.

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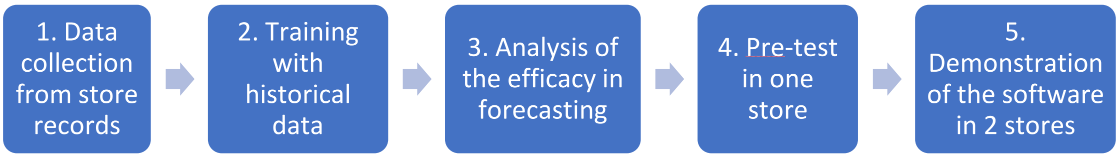
3. Structure of the demonstration

The purpose of the innovation is to support supermarket staff in their purchasing operations. The demonstration of this innovation in real supermarkets, in Italy, is the last of a series of actions, organised along five different steps (**Figure 1**).

1. collection of historical data from stores' records;
2. training of the forecasting algorithm with historical data;
3. analysis of the efficacy of forecasts, focused on a set of key products;
4. real-time test of the algorithm in one pilot store (pre-test);
5. demonstration of the software at two stores for a period of three months.

Figure 1: Steps needed to support the demonstration of the innovation



As for point n.1, a set of historical data was acquired from the records of 3 stores of the company supporting the demonstration and referring to the years from 2016 to 2022. Collected data included the code of the store, family, category and sub-category, product unique number, date of the sale, quantity sold, revenue, purchases, stock at the beginning and at the end of each month, data on promotions (beginning, ending, price and quantity sold), quantity of recorded waste, surplus of products (difference between purchases and sales), inventory gap (shrink), corresponding to quantities of products that are missing in the inventory (but never sold) at the monthly recording. In total, the dataset was composed by 2003 FFV products of which at least one sale was recorded, grouped in 109 families. The database included 497 products which are sold by the weight (data expressed in kg and €/kg) and 1506 products which are sold by the unit (data in number of packs and €/pack). Data on relevant products were used to train the algorithm.

In the meantime, a system to receive data and send forecasts to the stores has also been developed. Upon discussion with the retailer, it was decided to focus the implementation on a subset of 232 products which are considered more important in terms of turnover.

A pre-test in one store was conducted from 1 to 30 September 2023 to test the functioning of the forecasting software in a real situation (one PICO store). During this period, every morning, PICO sent an automatic email to SLU reporting the sales of FFV products of the day before; the algorithm acquired this information and, before h 9 am of the same day, delivered to the store an email with the sales forecast of the 96 products, in form of a csv

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file. These products were further selected, starting from the list of 232 products described above, based on historical data of 2021, having an annual turnover higher than 10,000 € and, at the same time, a rate of waste (calculated on historical data) exceeding 2.5%. For each product, the revenue and the mass of surplus products that becomes waste were calculated, summed up for the three stores. This data includes the total quantity of waste recorded for each product and the inventory gaps for the same products (corresponding to the unrecorded waste), summed for the three stores. A percentage rate of waste was also calculated, by dividing the mass of surplus that becomes waste, for each product, and the mass of the same products supplied to the three stores.

The food category manager of the involved store consulted the forecasts as an additional information to place the order of FFV for the next day (usually done between h9 and h11 am).

The pre-test done in September 2023 was followed by a set of follow-up meetings, between PICO and UNITUS and between UNITUS and SLU to identify the possible improvements for the next phase of full-scale demonstration.

The store staff involved in the first test suggested a new layout for the forecast file delivered by SLU every morning, to facilitate the consultation of data. A new sorting of the list of products was agreed upon, reflecting the structure of the ordering software they use. Also, the list of forecasted products would consist of only 40 products, dynamically selected each day based on what products recorded the highest sales the previous day. Of these, 30 slots were reserved for products sold by the kilogram, and 10 slots for products sold by the unit. Furthermore, products not ordered on a daily basis were excluded from the forecasts. The purpose of these changes was to ensure that the forecasts would always cover the products for which accurate ordering is more urgent.

Some further conditions were imposed on the product selection by SLU to ensure high quality forecasts. Products with insufficient training data, due to being rarely or never sold between 2016 or 2022, were excluded. Additionally, products that were suddenly among the top sellers but had no other recent sales data, were excluded for five days, because the forecasting model relies heavily on recent data points.

The full-scale demonstration started in the year 2024, on April 5th with one store, and the second store joined on April 17th. Daily forecasts were produced until the end of May.

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Figure 2 displays a screenshot of the forecast for 10 products from the 23rd of May 2024.

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Figure 2: A screenshot showing the 10 forecasting products from the 23rd of May 2024. REP, SR; FAM and ETI are codes used to identify the individual product. DES_ART and DES_ETI report the textual description of the product which has been hidden for privacy reasons; Q is the forecasted sales in quantity, as predicted by the software. AFFIDABILITÁ (1-10) refers to how reliable the forecast is.

forecast_20240523

IPER	REP	SR	FAM	ETI	DES_ART	DES_ETI	DATA	UNIT	Q	AFFIDABILITÀ (1-10)
1	20	255	3014	[redacted]	[redacted]		20240523	KG	28,57	8
1	20	255	3014	[redacted]	[redacted]		20240523	NU	22	7
1	20	255	3015	[redacted]	[redacted]		20240523	KG	10,90	8
1	20	255	3016	[redacted]	[redacted]		20240523	KG	6,16	7
1	20	255	3018	[redacted]	[redacted]		20240523	KG	8,16	7
1	20	255	3019	[redacted]	[redacted]		20240523	KG	26,11	8
1	20	255	3019	[redacted]	[redacted]		20240523	KG	9,31	7
1	20	256	3025	[redacted]	[redacted]		20240523	KG	9,48	7
1	20	256	3026	[redacted]	[redacted]		20240523	KG	11,94	7
1	20	258	3039	[redacted]	[redacted]		20240523	KG	17,92	6

4. Results of the demonstration

Performance of the software

The forecasts produced during the pre-test of September 2023 show in total an absolute error of 37% across all products. The error is based on the monetary sale value of all forecasted and sold quantities, rather than on the quantities directly. This conversion to monetary units acts as a normalization of the quantity measure, which otherwise is a blend of products sold by the kilogram and by the unit. The error is calculated by adding up the absolute difference between forecasted and actual sales, for each product and day during the period, and expressing this as a percentage of the total actual sales of all the forecasted products during the period.

The reliability of the forecasts can be compared to the naïve forecasting approach otherwise used by the stores, which considers sales data from the same week and weekday of the previous year. This forecasting approach resulted in an error of 57% during the period of pre-test in September.

The error was also calculated for each product individually. Among the 131 products sold on at least 15 days during the pre-test period, the forecasts yielded an average error of 43% (median error of 39%), compared to the naïve approach's average error of 66% (median error of 60%).

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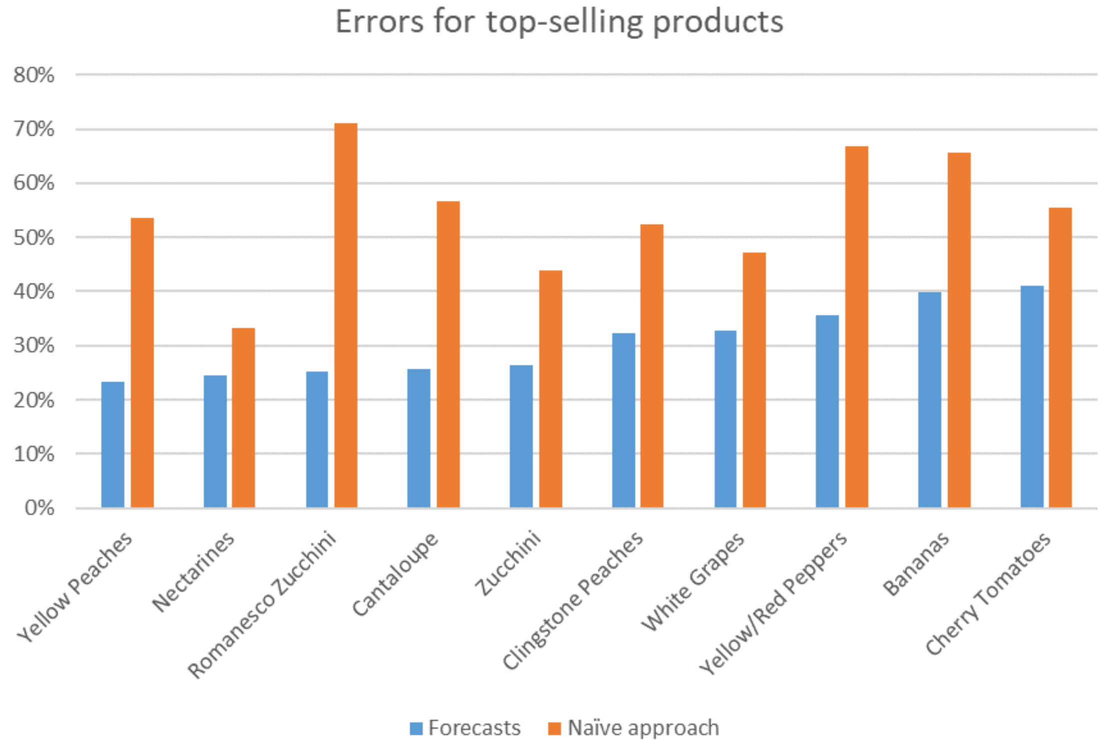
Figure 3 shows a comparison between the errors of the actual forecasts and the naïve approach, for the ten products with the greatest total sales during the pre-test period in September 2023.

Figure 3: Error comparison for the ten top-selling products during the first demonstration period.



During the demonstration period, in April and May 2024, the total error was 32% across all 113 forecasted products in both stores. For individual products forecasted at least 15 times during the demonstration period, the forecasts had an average error of 37% (median error of 36%) among 88 products.

The naïve approach could not be directly evaluated for the demonstration period, because sales data from the previous year was not available. During the years 2017 to 2022, where sufficient data is available, the naïve approach resulted in an error of 55% during the months of April and May, considering only products that were forecasted in the second demonstration period. For the 88 individual products evaluated for the forecast, the naïve approach historically had an average error of 62% (median error of 55%) in April and May. The products excluded don't lack 15 data points 2017-2022, but lack enough data during the demonstration period, so that the error is measured for the same 88 products, enabling as fair a comparison as possible.

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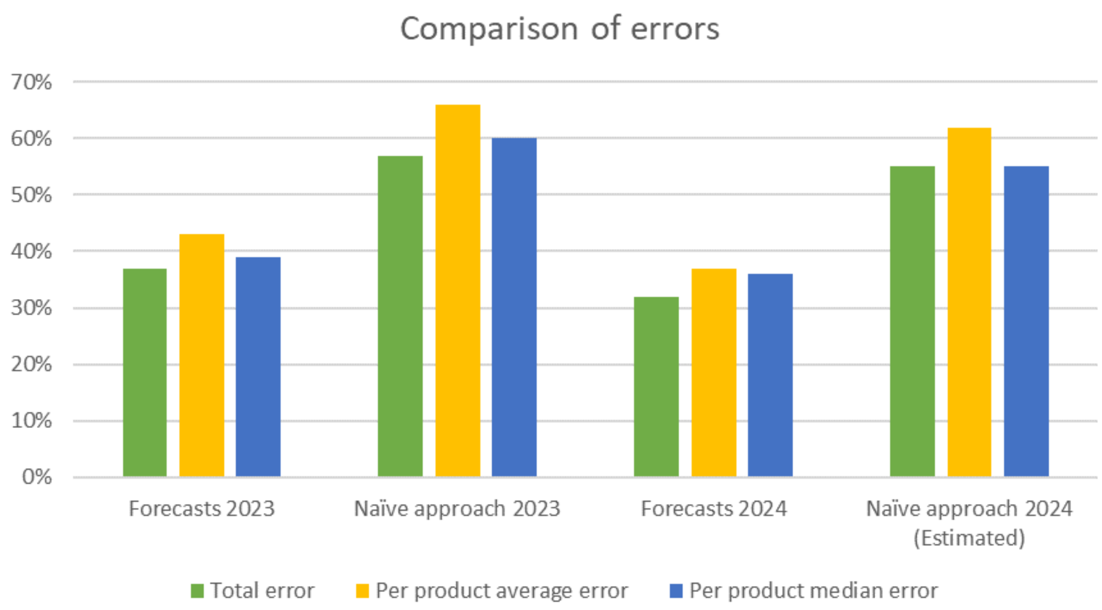
All the different error rates, for both demonstration periods, are presented in Figure 4.

Figure 4: A visual comparison between the forecasts and the naïve approach, for the two demonstration periods. For the per product average, the error is calculated the same way, but for each product individually. I.e., adding up the absolute difference between forecasted and actual sales for each day during the period, and expressing this as a percentage of the total actual sales of that specific product during the period. The average of each such error is the per product average error.



Qualitative feedback from stores' staff

After the conclusion of the demonstration, the staff who participated in the demonstration – namely, the fruit and vegetable category managers of the two stores – were invited to share their experiences in a dedicated meeting with UNITUS. This discussion was useful to gather the feedback of the two category managers and evaluate area of improvement for the software.

During these meeting, they described their daily routine of ordering FFV, before starting the demonstration. The choice of the quantity of each FFV to be ordered for the next day considers the following key factors:

- Sales of the previous day
- Quantity in stock

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- Weather conditions and seasonality
- Sales from the previous year
- Day of the week (including holidays)
- Risk of having a surplus

Together with their wide experience and knowledge of the market dynamics, the software provided an additional supporting information during the ordering process. Therefore, the daily routine of ordering FFV during the demonstration remained the same, but an additional information was considered: the sales forecast provided by the software every morning.

Overall, they expressed a general satisfaction for the performance of the software. It was well-received by the store staff in charge of making the orders of fruits and vegetables. Food category managers perceived the forecasts as “accurate” for 80% of the days. The reliability of the software was highlighted, and it was deemed useful to make more accurate ordering decisions. They highlighted the importance of considering seasonality and sales prices, especially for promotions, to enhance forecast reliability. Overall, the software proved to be a valuable tool for making more precise orders, reducing food waste, and supporting store managers in their decision-making processes.

List of Products

The forecasts focused on a dynamic list of products, updated daily based on the previous day’s top sellers. Managers suggested adapting the product list to account for seasonal and weather-related variations. Indeed, upon they experience the highest risk of surplus ordering is encountered for the products that have a high seasonality. They also highlighted that promotional pricing is one of the main factor affecting sales volumes. Therefore, carefully including promotions among the factors considered by the software is crucial for the accuracy of the software. Promotions that are planned in advance are considered in the forecasts. In few cases, promotions are decided “on the spot” when there is a significant surplus of product in stock. These unplanned promotions could not be included in the forecasts and might have affected their reliability. Incorporating this additional information among the variables considered by the software could improve forecast accuracy.

Handling surplus and waste

For surplus products, managers used to reduce the quantity ordered if the sales of a product dropped over the last 2-3 days, and strategically place surplus products in the store to minimize waste.

In the case that the products are not sold and must be discarded, those are sorted into the organic waste collection. Currently, we are informed that in both municipalities, there are no active regulatory measures that imply a discount on correctly sorted waste by commercial activities, commonly known in Italy as the Gadda Law.

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Outlook

The successful demonstration of the forecasts suggests that, with further refinements, the software could be implemented on a larger scale across Italian supermarkets, contributing significantly to more sustainable food supply chain management. This kind of systems are currently in use in many other European countries to support accurate ordering in order to reduce waste and increase profitability (Schneider and Eriksson, 2020).

5. Conclusions

The forecasting software developed in this task was developed and trained to predict sales of fruits and vegetables in supermarkets. This has proven to be successful from a technical point of view and the forecast model provided by the software achieved a total absolute error of 32% in predicting sold quantities across all products in both stores, with the error calculated based on their monetary sales value. This represents a significant improvement over the baseline model currently used by the stores, which historically achieves an error of 55% for the same products and during the same months.

However, any technical aid is highly dependent on the trust and skills of the user. To this regard, the approach of the food category managers showed a good openness to innovation, considering the tight schedule they have to complete the ordering process on time. The trust towards the forecasts increased during the demonstration, as they could see that the forecasts approached to a high extent the actual sales recorded in the FFV department.

In the end, the demonstration revealed that having access to reliable forecasts, timely in the morning, can support food category managers' decisions about ordering, thus facilitating their job. The software demonstrated to be a valid support to decision-making, although the experience and know-how of food category managers remains the pivotal aspect to assure a proper ordering process.

Based on these results, some feasible improvements to the innovation are suggested, especially focusing on seasonal and weather-related products, which seem the be the main concern of food category managers, for the high fluctuation of the demand of these products.

Considering that in the Italian retail sector the use of this types of software is not diffused at all, we also see a high potentiality of replication in this country.

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