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The Development of a Prediction Model Related to Food Loss and Waste in Consumer Segments of Agrifood Chain Using Machine Learning Methods

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Abstract: Food loss and waste (FLW) is a primary focus topic related to all human activity. This phenomenon has a great deal of importance due to its effect on the economic and social aspects of human systems. The most integrated approach to food waste analysis is based on the study of FLW alongside the agrifood chain, which has also been performed in previous studies by the authors. This paper presents a modality of determination of food loss and waste effects with an emphasis on consumer segments in agrifood chains in the form of a predictive model based on statistical data collected based on specific methods in Romania. The determination is made comparatively, using two predictive machine learning-based methods and separate instruments (software), in order to establish the best model that fits the collected data structure. In this matter, a Decision Tree Approach (DTA) and a Neural Network Approach (NNA) will be developed, and common methodologies of the approaches will be applied. The results will determine predictive outcomes for a specific food waste (FW) agent (e.g., consumer) based on pattern recognition of the collected data. The results showed relatively high-accuracy predictions, especially for the NN approach, with lower performances using the DTA. The effects of the application of this predictive model will be expected to improve the food loss prevention measures within economic contexts when applied to real-life scenarios.

Keywords: food waste; food loss; predictive model; neural network; decision tree; economic behavior; agrifood chain; consumer

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1. Introduction

The determination of the implications of food loss and waste (FLW) dynamics [1] within economic contexts is an imperative task due to the rising resource optimization needs [2] in the actual agrifood chain. Understanding the implications of this phenomenon [3] can lead to great improvements in efficiency across all sectors of the agrifood chain [4]. In this matter, the agrifood chain dynamics reveal a great deal of underlying causes and effects of FLW, and their study can bring novel approaches to the prevention [5] of this phenomenon. These approaches must deal with the fidelity of the models related to real scenarios, in the context of challenges related to FLW study (e.g., data collection [6], agrifood chain complexity, etc.).

Food loss and waste is a complex matter that encompasses an extended range of areas and stakeholders. For the current study, the emphasis was put on the consuming part due to it having the greatest impact on all stakeholders within the agrifood chain, but also due to its relation to the initial objective of the study, oriented toward the study of consumer food consumption behavior. However, an integrated agrifood chain approach was followed within this context by establishing the causes and effects of food waste alongside the food chain, a topic that was studied extensively in previous papers and is summarized in Section 2.1.1. This methodology followed a direction that is commonly used in the literature, with the most integrated direction of study being related to agrifood chain analysis (Food Supply Chains—FSC [7]). This approach is widely studied in the literature due to the holistic characteristic of the approach and the complex relationships established alongside the chain. Thus, one of the most important characteristics of an FLW study relies on the integrated approach.

Another important element of the FLW phenomenon is related to food security and environmental sustainability [8]. Food security relies on several factors, including the rational use of resources, in order to provide the necessary amounts of food for the entire population. In this matter, FLW has the opposite effect, also having an impact on the environment [9]. Strategies for FLW reduction also lead to environmental sustainability, as well as the assurance of better food stability.

Also, the environmental effects of FLW can be addressed by using Life Cycle Assessment (LCA) approaches. LCA is a methodology for examining environmental impacts [10] associated with FLW management. Thus, using LCA approaches can lead to FLW prevention and reduction. This leads to the main principle of the circular economy, which encompasses the idea of the reuse of waste at every step of the agrifood chain as a material or flow of energy in the industrial or economic process [11].

As a result, food loss and waste management comprises several strategies that are mentioned and researched in the literature, related to prevention (one of the most efficient strategy approaches) [12], reuse, and reduction [13]. In [14], a brief study of FLW in the context of food security was conducted, with conclusions related to zero levels of FLW, showing that a link to food security policies [15] is essential in this FLW management. Several strategies related to FLW management are compiled in the literature, such as:

- The identification of FLW's causes [16].
- The participation of the stakeholders' human resources in instructional initiatives (e.g., courses) [17] related to FLW.
- The application of food production optimization [18] methods and techniques.
- The development of logistic [19] methods (e.g., location of processing plants near farms, effective packaging [20] and labeling, etc.).
- The development of analysis initiatives within the production systems of agrifood chain stakeholders related to the prevention, prediction, and reduction of food waste using various tools (e.g., econometric, digital [21], machine learning based, etc.).
- The inclusion of better consumer informational strategies in the shelf-related phases (processing and purchasing processes) from all the agrifood chain stakeholders [22].
- The development of initiatives for the creation of a food culture related to the consumer based on social [23] and economic [24] premises.
- The redirection of unconsumed but still suitable-for-consumption food products destined for food waste to food banks [25] or the usage of spoiled food products for environmental [26] processes (e.g., compost obtaining, biofuel generation, etc.).
- The development of circular economy principles [27] within the agrifood chain.

Thus, in the context of digital development, one of the most efficient strategies for FLW prevention and reduction is related to the usage of digital tools, especially machine learning tools, such as classification or prediction tools. In this matter of FLW management, the main purpose of this paper is the development of a prediction model related to food waste on the consumer level of the agrifood chain, with implications for all agrifood chain levels. Also, other objectives include:

- The development of a mapping model related to the relationships between behavioral, social, and economic factors and food waste amounts.

- The determination of the efficiency of machine learning approaches in the determination of causal analysis of FW.
- The determination of the accuracy of specific machine learning methods in the development of the mentioned prediction model.

This paper presents the development of a prediction model related to specific parts of the agrifood chain, mainly concentrated on the consumer segments and their behavior [28]. The prediction phase refers to the determination of consumers' tendency to generate food waste and its intensity based on specific indicators. The paper is related to the final stages of a broader research initiative related to the study of food loss and waste alongside the agrifood chain. The previous papers that are part of this research initiative are related to the development of analyses and the formulation of models that can provide a deeper understanding of the phenomenon. In this matter, statistical methods and tools for the analysis were used and various modeling strategies and tools were chosen (e.g., graph theory, Petri nets, etc.). These findings, presented in the following section, also serve as key findings in developing the prediction models presented in this paper. The central data source used for the development of the model includes the results from a questionnaire (survey of Supplementary Materials [29]) related to demographic data, purchasing habits, and food waste perception. The data are presented extensively in Section 2.1.2. The results will be presented in Section 2.1.1.

This paper consists of the development of a prediction model that will also contain a comparative analysis of two main prediction tools in order to establish the best configuration of the prediction results. In this matter, two prediction methods are chosen: a Decision Tree Approach (DTA) and a Neural Network Approach (NNA). This choice arises from the rationality of choosing machine learning methods over other prediction methods (e.g., econometric methods, regression models, etc.). The first argument is related to the determination of the complex relationships between the considered variables and the potential for higher accuracy, despite the low volume of the data obtained and used for the development of the models. These two approaches were also chosen due to their versatility, commonality, and match with the current input data configuration. In this matter, the DTA was chosen for the potential for interpretability and simplicity of the results-obtaining process, while NNA was chosen in order to determine complex nonlinear relationships between given factors. These methods will be applied to a specific set of input data resulting from statistical research, whose main configuration will be presented in the next section. Neural network models [30,31] and decision tree models [32] are part of the machine learning (ML)-based tools used for the automation of tasks such as classification, regression, or prediction.

There are specific assumptions developed based on the analysis of a dataset compiled from demographic and behavioral variables obtained from the collection of data from consumers. Throughout the entire project, some of these assumptions were studied. In previous research papers related to this project, the following assumptions were studied:

- Food consumption behavior, habits, education level, and socio-economic factors, as well as production and logistic factors of the food products, have a significant impact on food loss and waste alongside the agrifood chain (a1).
- The food waste quantities can be lowered at any level of the agrifood chain, with a chain reaction occurring if FLW is reduced in any part of the chain. Moreover, a greater leverage effect related to FLW reduction is obtained as we move down the agrifood chain (a2).
- The prediction models can be used to optimize the FW (directly) and FLW (indirectly) reduction methods (a3).

These assumptions are important for this research as a foundational base for the development of the model. For the specific research described in this paper, the assumptions related to prediction models are:

- The machine learning models can predict FW patterns with a high degree of accuracy (a4).

- The two approaches (DTA and NNA) are suited to the development of prediction models for FW (a5).
- There are significant differences between the two approaches related to the prediction results on the given topic and the dataset used for the research (a6).

The first three assumptions were established as starting hypotheses and dealt with in previous papers related to this project and will be mentioned in this paper in their respective places. The current model development process does not include the study of these three assumptions (a1, a2, and a3), as they were studied in previous papers. The latter three (a4, a5, and a6) consist of assumptions that will be questioned and researched in this paper. The formulation of these assumptions was based on our own ideas and results, and a subsequent literature search was conducted to find studies that confirm or are consistent with these:

- Related to the potential of machine learning models in consumer FW reduction, the research present in the literature is centered on food demand forecasting and shows that accurate forecasts of food demand can enhance the service quality of food services by ensuring better availability while simultaneously minimizing food waste [33]; classification-based approaches are increasingly employed to predict food consumption patterns, aiding in efficient food management and reducing surplus [34] (a4).
- Specific models can be used for various situations, with promising results being determined for supervised learning models, including linear regression, decision trees, and neural networks, which can utilize historical sales data to forecast future demand effectively [35], and the findings from utilizing forecasting machine learning models for meal planning during crises have validated their effectiveness [36]. Other studies showed good results related to the goodness of fit for neural network-based models [37] and tree-based models [38] (a5).
- Related to machine learning prediction tool performance, promising results based on training data structure were obtained [39], and the importance of the comparison of the tools is essential [40,41] (a6).
- Subsequently, the hypotheses were formulated based on these assumptions. These hypotheses are:
- H1: The machine learning models can predict FW patterns with a high degree of accuracy.
- H2: The two approaches (DTA and NNA) are suited for the development of prediction models for FW.
- H3: There are significant differences between the two approaches related to prediction results on the given topic and the dataset used for the research.

The development of prediction models has garnered extremely broad interest in the literature due to its connection to the development of Artificial Intelligence tools. In this matter, prediction is used widely in areas related to:

1. Finance: prediction models are used to forecast stock prices [42], assess credit risk, and optimize trading strategies [43].
2. Healthcare [44,45]: models assist in diagnosing diseases, predicting patient outcomes, and personalizing treatment plans.
3. Marketing [46] and retail [47]: models are employed to forecast consumer behavior, personalize recommendations, and optimize inventory management [48].
4. Supply chain: models are used to anticipate demand [49], optimize supply chain operations [50,51], and manage inventory levels.
5. Weather [52]: models in meteorology forecast weather conditions [53,54], including temperature, precipitation, and severe weather events.
6. Transportation: models assist in traffic management [55], route optimization [56], and autonomous driving systems.
7. Education: models are applied to personalize learning experiences [57], predict student performance [58,59], and manage educational resources.

One of the direct implications of the usage of predictive models is related to consumer behavior [60], purchasing routines [61], food waste habits [62], and food consumption dynamics [63,64]. In this matter, these can have indirect effects on previous links in the agrifood chain, taking advantage of prediction tools [65,66].

The obtained results show a robust model for the current dataset, with a great deal of potential for improvement. Such comparisons are modeled using specific methods, such as in [67]. Also, another important direction of development related to the performance of the model will be determined by analyzing the comparison between machine learning approaches and other approaches (e.g., statistical, econometric, pattern recognition, or other methods, such as the STIRPAT model or the ARIMA model [68]). The NN Approach was determined to have a better performance and the DT approach had the potential to be greatly improved. In this matter, a similar study of complex models shown in [69] can be used to assess food waste.

The model would be used to increase the efficiency of all agrifood chain sectors [70], from farmers with their agricultural needs [71] to producers, processors, and consumers, with a direct impact on consumption, economic [72], and social [73] sectors, as well as those related to product and life cycle assessment [74].

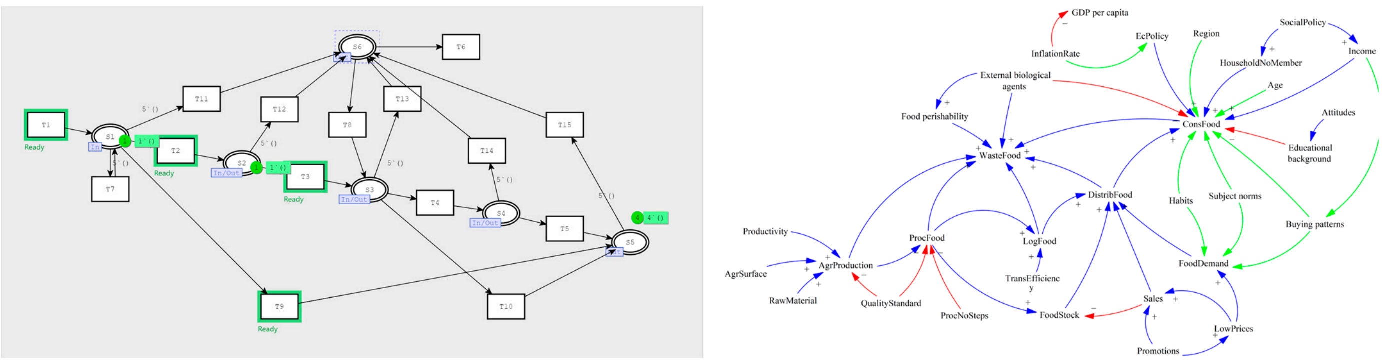
2. Materials and Methods

The main aspects of the paper's methodology are related to three main areas: the collection and processing of data used for the development of the model, the construction of the two model approaches based on DT and NN, and the comparative analysis of the results in order to obtain the best model configuration. This section is structured around the (Section 2.1.1) presentation of the data and data models resulting from the data processing built for the study of FLW alongside the agrifood chain and (Section 2.1.2) the presentation of the data related to the consumer part of the agrifood chain, resulting from the application of a questionnaire to a specific consumer group.

2.1. Data Used for the Development of Machine Learning Models

2.1.1. Data Related to Agrifood Chain

Related to food loss and waste alongside the food chain, previous research has determined several models that would address the behavioral aspects of the agrifood chain system. These were determined using specific tools (Petri nets, graph theory [75], and system dynamics [76,77]). The results of two models built in the previous paper are shown in Figure 1 and described in the next two paragraphs.



(**a**) (**b**)

Figure 1. The models of agrifood chain dynamics related to food waste: (**a**) the model built using Petri nets and graphs; (**b**) the cause–effect diagram of the model built using system dynamics.

The main purpose of the study related to the usage of Petri nets (shown in Figure 1a) was to analyze the waste cycle within an agrifood chain, focusing on food loss and waste, in order to establish the best practices for managing food waste in the agrifood industry.

In the figure, the links to the agrifood chain (e.g., farmers) are defined as states (S), and the actions (A) made between states are modeled as transitions (T). The arcs are defined as connection links between specific places and transitions. For instance, T1 is connected to S1, indicating that raw material is generated by agricultural processes, and the food state in the agrifood system is "Raw material on farm".

Related to the study describing the causes and effects of FLW using system dynamics (shown in Figure 1b), this model illustrates the complex agrifood chain and its interactions related to food waste. The chain begins with agricultural production (AgrProduction) and raw materials, proceeding through food processing (ProcFood), distribution (LogFood), and retail sales (DistribFood) to consumers (ConsFood). Food waste (WasteFood) is influenced by various factors, including processing and distribution efficiency, food stocks, food demand, and consumer behavior. Consequently, food waste impacts inventory, costs, and waste awareness. Farmers, as producers of raw materials, significantly influence the entire agrifood chain. By analyzing feedback and interactions, this model underscores the necessity for effective resource management, consumer education, and collaboration across all levels of the agrifood chain to reduce food waste, yielding social, economic, and ecological benefits.

One of the main interpretative directions focuses on operational efficiency, achieved by identifying the critical points where waste is generated in large quantities. The second interpretative aspect pertains to recycling processes within the system. The models include specific states related to recycling activities at the farm and processing levels, highlighting their importance and quantifying their impact. In this matter, these studies were employed to confirm the assumption (a2) stated in Section 1 (Introduction).

The data presented in this section has an essential role in the development of DTA and NNA models:

- Firstly, the models were aimed to emphasize the effect of food waste on previous levels of the agrifood chain based on specific methods (system dynamics and Petri nets). This research is essential to determine a base for the motivation of the current food waste-based study, due to the fact that food waste reduction has the potential to lead to food loss reduction alongside the agrifood chain.
- Secondly, the data obtained in this research are valuable for the establishment of food waste and food loss dynamics in the agrifood chain. These data have a more qualitative characteristic, thus serving as a preliminary study used to make specific decisions for the DTA and NNA methods (e.g., the choice of specific causes of food waste).

Thus, the data presented in this section are important as they create a foundational conceptual base for the development of DTA and NNA models.

2.1.2. Data Related to Consuming Sectors

The first important aspect is related to data collection and processing. The data were determined for the entire agrifood chain, with a concentration on the consumer part. The data belong to several categories:

1. Statistical historical data related to food waste and economic trends related to causes and effects.
2. Statistical data obtained based on the implementation of a questionnaire related to consumer food waste behavior.
3. Data obtained after the application of specific methods:
    - FLW factor determination.
    - System dynamics-based cause and effect diagrams.
    - Statistical correlations between economic food loss and waste indicators.
    - Structured data in the form of graphs and Petri nets.
    - Preliminary classification data using multivariate clustering analysis.

All the data presented above are structured in Table 1, which presents the various sources of data used for the development of the prediction models. The main data source used for the development of prediction models was related to the questionnaire (survey of Supplementary Materials) responses (shown in italic characters in Table 1), which were then correlated with other statistical and historical data and processed using various tools (e.g., factorial analysis, system dynamics, HCA, Petri nets, etc.).

Table 1. The data obtained after the application of specific methods in previous research papers.

Data Category	Data Source	Data Generation Method	Resultant Data	Resulted Data Form
Statistical data	Historical datasets	Direct observation and collection	Economic (e.g., GDP per capita), social and environmental indicators	Plots
Statistical data	*Questionnaire*	*Collection*	*FLW behavior indicators*	*Plots*
FLW factor determination	Literature review	Factorial analysis, correlation	Correlation data between factors and FLW amount	Plot, factor diagram
Cause and effect	FLW factor determination	System dynamic	Cause and effect influences	Cause and effect diagram
Structured data	Literature review, FLW factor determination	Petri nets, graph structures	Agrifood chain dynamic	Petri net
Clusters	Questionnaire	Hierarchical Cluster Analysis (HCA)	Consumer-related FW clusters	HCA dendrogram

The data were processed, analyzed, and studied in previous papers [78,79]. The primary data used in this study are related to the statistical instrument in the form of a questionnaire, which was used to collect data from a definite number of respondents. One of the characteristics of the collected data is its cross-sectional aspect. The questionnaire was administered in an online environment, using specific survey software (in this case, Google Forms—https://forms.google.com), taking into consideration the typical rules related to the design and implementation of a typical survey. The questionnaire used in this study was generated using Google Forms, an accessible tool for creating surveys and collecting data. Google Forms was selected due to its ease of use and the ability to reach a broad audience, allowing for efficient data collection and organization and ensuring that the data collection process was both efficient and effective.

Statistically, the sample of 365 respondents is indicated to approximate the minimum sample size given for a confidence level of 95%, a margin of error of 5%, a population proportion of 50%, and an unlimited population size. The calculated value using the formula in Equation (1) is 385; thus, the sample can be considered statistically significant in terms of volume.

$$n = \frac{z^2 \times \hat{p}(1 - \hat{p})}{\varepsilon^2} \quad (1)$$

The parameters of the Equation (1) are described as follows:

- n: sample size.
- z: Z-score, which corresponds to the desired confidence level (a 95% confidence level corresponds to a Z-score of approximately 1.96).
- $\hat{p}$: estimated proportion of the population (sample proportion). This is an estimate of the proportion of the population, considered to be 0.5.
- ε (epsilon): the desired margin of error, in this case, 0.05.

The data collected from the questionnaire contain three main important sections:

1. Demographic data, related to information such as age group, gender, studies, or income, presented in Figure 2.
2. Data related to food-purchasing habits (e.g., proportion of food costs from the total income, food purchasing places, etc.), presented in Figure 3.

3. Data related to food waste perception (e.g., amount of food waste, food waste types, etc.), presented in Figure 4.

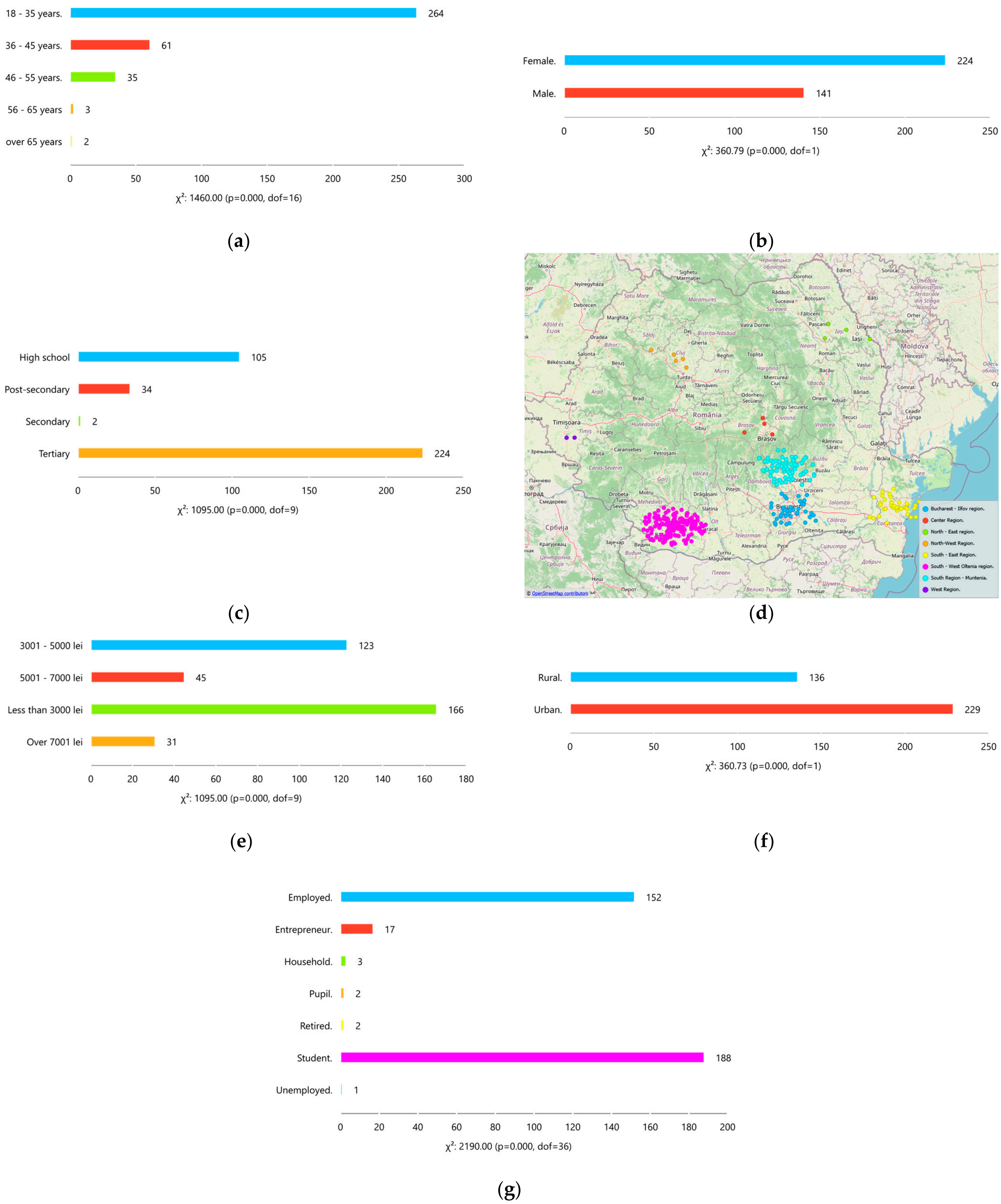


Figure 2. The presentation of the demographic characteristics of the sample group: (**a**) age; (**b**) gender; (**c**) formal education level; (**d**) NUTS-2 geographical distribution; (**e**) monthly income; (**f**) residence; (**g**) socio-economic category.

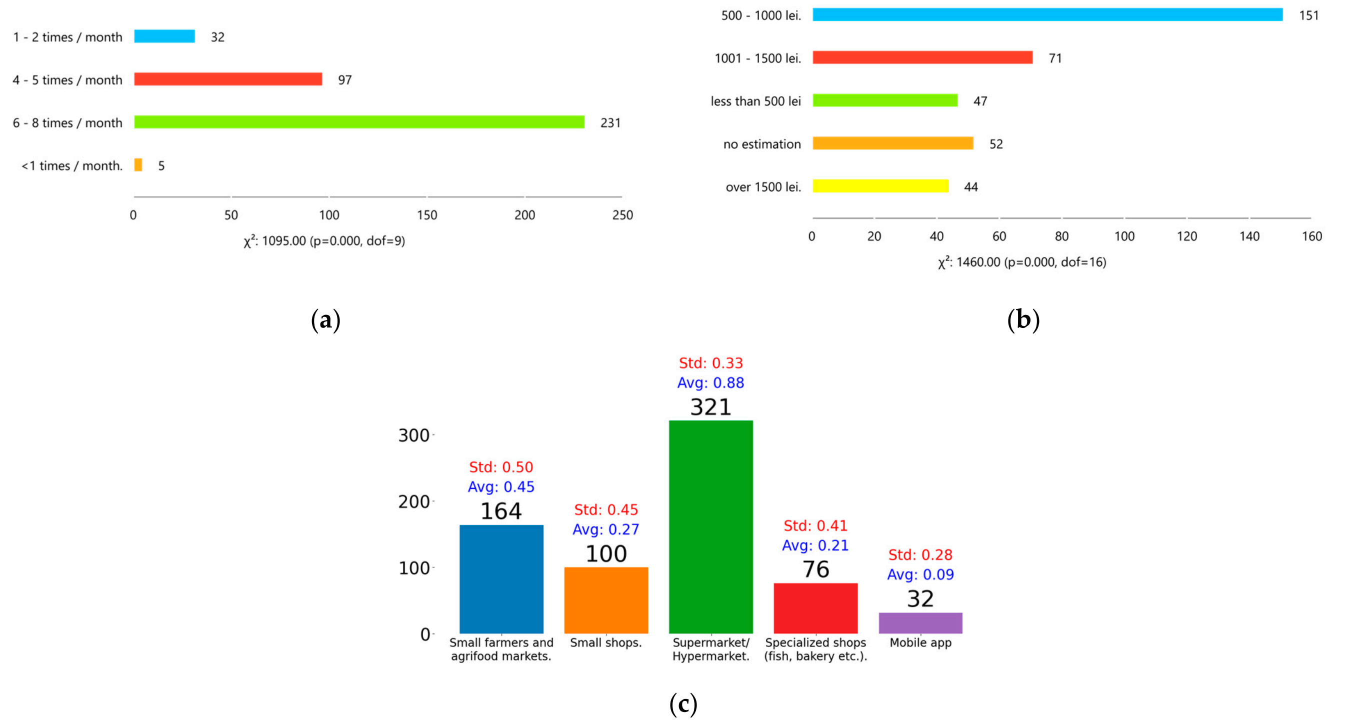


Figure 3. The presentation of the food behavior indicators of the sample group: (**a**) frequency of food purchasing; (**b**) amount of money spent on food; (**c**) places chosen for food purchasing.

The demographic data presented above show aspects of the sample group related to their social characteristics. In this matter, we can observe that a large proportion of the respondents are situated in the 18–35 years age group (approximately 73%), suggesting that younger age groups were more inclined to participate in the study. Regarding gender, women are more represented at slightly over 60%. As for education level, a large proportion of the respondents had attained a tertiary level of education (ISCED levels 5 to 8), indicating a good conceptual understanding of the topic of food waste. The respondents are concentrated geographically in the South-West Development Region in Romania, presenting a fairly low-balance geographical distribution. The indicator related to monthly income is relevant to food purchasing, given the large amount of food expenses in the personal budget. According to this indicator, approximately half of the respondents earn less than 3000 lei, leading to the assumption that the respondents have a more prudent approach to food waste. Also, a large part of the sample group comes from urban areas and from the blue-collar socio-economic category.

The second category of data, shown in Figure 3, presents several indicators related to food behavior. This behavior was defined in the research by three indicators: the frequency of food purchasing, the amount of money spent on food, and the places attended for food purchasing.

As we can see and as expected, the frequency of food purchasing is a relatively high factor, with most of the respondents buying food as frequently as 1 to 2 times a week (corresponding to 6–8 times per month). Also, the most numerous group of respondents spends an average amount of 500–1000 lei (Romanian currency) on food, or around 100–200 euros per month. Finally, the most attended places for food purchasing were established to be supermarkets/hypermarkets or directly from small farmers.

Figure 4 presents indicators related to food waste, such as the main perceived causes of food waste, the perceived proportion of food waste from the total food quantity, and categories of wasted food.

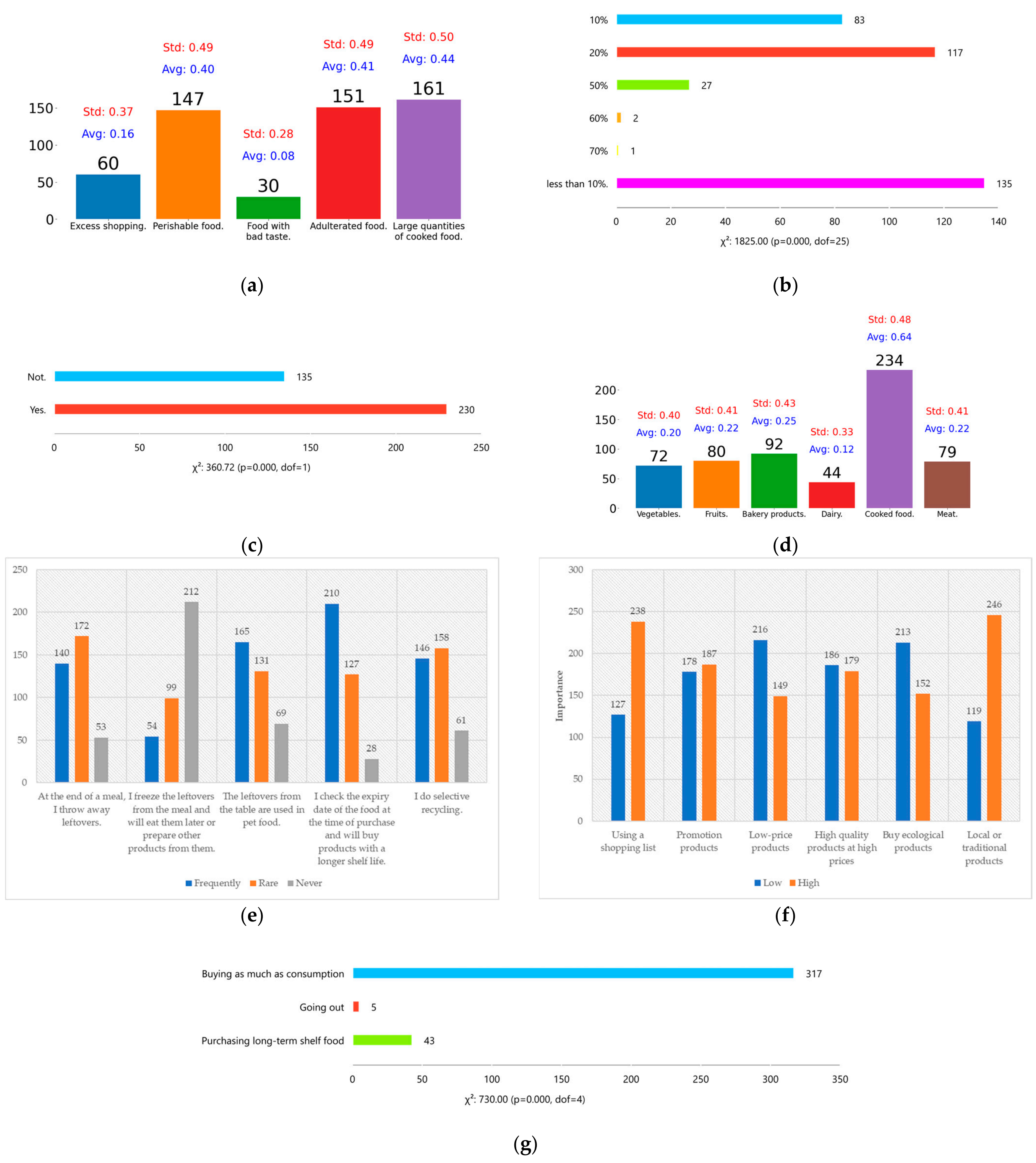


Figure 4. The presentation of the food waste behavior indicators of the sample group: (**a**) main perceived causes of food waste; (**b**) perceived proportion of food waste from total food quantity; (**c**) the proportion of respondents who waste unconsumed food; (**d**) categories of wasted food; (**e**) responses given to affirmations related to food waste; (**f**) aspects taken into account by respondents in the food purchasing process; (**g**) identified measures to reduce food waste.

According to the food waste indicators in the research, the majority of the respondents have a responsible attitude toward food waste, with limits regarding their time management. In this matter, a large number of respondents think that they waste unconsumed food, but in a small proportion (up to 10%) of the total quantity of purchased food. Regarding food categories, a great deal of wasted food consists of cooked food, meat, and dairy products. Related to this, the main perceived causes of food waste were determined to be the large amounts of purchased and cooked food and the foods' perishable characteristics. The respondents also rarely throw away leftovers, almost always using them to prepare other products, Also, they tend to use food waste as pet food and to check the expiry date of the food. Selective recycling is rarely performed. Amongst the food-purchasing habits related to food waste, respondents determined the usage of a shopping list, the purchase of local products, and rarely buying low-price or ecological food as usual purchasing actions made to reduce food waste.

Related to data collection guidelines, the ethical and legal aspects of data collection were taken into consideration. In this matter, respondents were informed of the purpose of the data collection process, and consent related to their participation was established. Also, the data were anonymized, which further established the legal and ethical aspects of the data collection process.

The data from the questionnaire were also pre-analyzed using the Hierarchical Cluster Analysis (HCA) method, from which we determined several clusters of respondents [80]. The obtained data are shown in Figure 5.

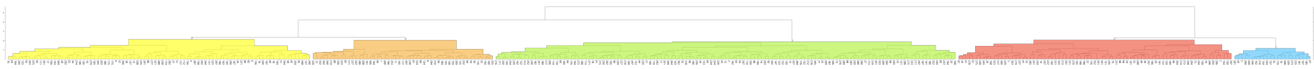


Figure 5. The dendrogram resulting from the Hierarchical Cluster Analysis, which shows the consumer clusters based on their food waste behavior.

Cluster C1, with 22 respondents, is characterized by frequent food purchases, low food waste perception, reuse of leftovers (mainly for pets), preference for long shelf-life products, and selective recycling, with food spoilage after cooking as the main cause of waste. Cluster C2, with 77 respondents, is marked by frequent food purchases, high or overestimated spending, 10–20% perceived food waste, moderate leftover disposal with some preservation for future use, preference for long shelf-life products, and unpredictive recycling behavior, with perishability and excess cooked food as the main cause of waste. Cluster C3, comprising 129 respondents, frequently buys food with a budget of 500–1000 lei, has 20% food waste, rarely preserves leftovers, prefers long expiry dates, has moderate recycling habits, and mainly wastes food due to excess cooked quantities that spoil. Cluster C4, with 51 respondents, buys food 4–8 times per month with a budget below 1000 lei, has less than 10% food waste, rarely preserves leftovers, prefers long-lasting food, has unpredictable recycling habits, and mainly wastes food due to spoilage of large, cooked quantities. Cluster C5, with 85 respondents, frequently buys food with a budget between 500 and 1000 lei, has 10–20% food waste, unpredictably keeps or uses leftovers for pets, prefers long-lasting food, and has uncertain but slightly inclined recycling habits, with perishability as the main cause of waste.

The cluster determination was a preliminary phase in the development of the prediction models, playing the important role of outlining the most important characteristics or variables that should be taken into consideration for these models. At the same time, this preliminary research provided insightful conclusions related to the confirmation of the first and third assumptions (a1 and a3) stated in Section 1 (Introduction).

2.2. Prediction Model Approaches

2.2.1. Neural Network Approach Methodology

The prediction model represents a crucial component of the exploratory phase of the overall model. Its primary objective is to identify and analyze specific patterns of food waste (FW) associated with the consumption stage of the agrifood chain. By focusing on the consumption component, the model aims to uncover distinctive trends and behaviors that contribute to FW during this phase. The main expected outcomes include a comprehensive understanding of these patterns, which will be instrumental in addressing and mitigating the FLW phenomenon effectively at the consumption level. To achieve this, the following steps, also presented in their primary form in [79], were undertaken:

1. Data Selection: Specific characteristics relevant to the model were chosen from all given responses. These characteristics serve as the indicators forming the basis of the prediction.
2. Data Pre-analysis: Statistical correlations between the selected data were explored and identified. These correlations help establish a categorical structure that defines specific behavioral patterns used in the output process (e.g., clusters or classes as patterns for prediction).
3. Data Preprocessing: The selected data underwent transformation processes such as normalization and encoding.
4. Dataset Split: The dataset was divided into two subsets: a training set and a testing set, typically in 80–20 or 70–30 proportions. The chosen proportion is 80–20.
5. Model Building: The chosen method (a neural network) was used to build and train the prediction model using the training data.
6. Model Assessment: The model was evaluated using specific KPI indicators measured against the testing data.
7. Model Interpretation: The results were interpreted, and the model's parameters were optimized.

Thus, starting from the selected characteristics that influence FW behavior and the obtained data, the prediction model identifies patterns related to food waste, either as numerical predictions (e.g., a predicted quantity of food waste) or categorical patterns (e.g., a cluster of food waste behavioral patterns).

As for the architecture of the neural network, the following characteristics can be presented:

1. 365 input data entries, corresponding to the presented input data.
2. 34 features, categorical data, corresponding to the independent variables.
3. 1 target feature, categorical data, corresponding to the dependent variable (FWP), with 6 categories codified from 1 to 6.
4. Four layers of neurons:
    - The input layer with 34 characteristics, presented in detail in Table 2.
    - The first hidden layer with 128 neurons, dense (fully connected layer), with the ReLu (Rectified Linear Unit) activation function.
    - The second hidden layer with 64 neurons, dense, with the ReLu activation function.
    - The output layer with 6 neurons, dense, with the Softmax activation function. The 6 neurons correspond to the possible values of the dependent variable. The Softmax function transforms the output array into a probability array, which contains the probability of the input data falling into each of the six categories.

Table 2. The variables used in the two models and their descriptions after the first encoding process.

No.	Variable		Abbreviation	Possible Values Set
1	Age category		Y	{1, . . ., 5}
2	Formal education level		E	{1, . . ., 4}
3	Socio-economic category		S	{1, . . ., 7}
4	Monthly income		I	{1, . . ., 4}
5	The food purchase frequency		FPF	{1, . . ., 4}
6	Places for food purchasing-choice	Small farmers and agrifood markets	P1	{0, 1}
		Small shops	P2	{0, 1}
		Supermarket/Hypermarket	P3	{0, 1}
		Specialized shops (fish, bakery, etc.)	P4	{0, 1}
		Mobile app	P5	{0, 1}

Table 2. *Cont.*

No.	Variable		Abbreviation	Possible Values Set
7	The amount of money used for food purchase		FPM	{1, . . ., 5}
8	Aspects taken into account by respondents in the food purchasing process	Using a shopping list	FPA-1	{0, 1}
		Promotion products	FPA-2	{0, 1}
		Low-price products	FPA-3	{0, 1}
		High-quality products at high prices	FPA-4	{0, 1}
		Buy ecological products	FPA-5	{0, 1}
		Local or traditional products	FPA-6	{0, 1}
9	The cause of food waste-choice	Excess shopping	FWC-1	{0, 1}
		Perishable food	FWC-2	{0, 1}
		Food with bad taste	FWC-3	{0, 1}
		Adulterated food	FWC-4	{0, 1}
		Large quantities of cooked food	FWC-5	{0, 1}
10	Categories of wasted food	Vegetables	C1	{0, 1}
		Fruits	C2	{0, 1}
		Bakery	C3	{0, 1}
		Diary	C4	{0, 1}
		Cooked food	C5	{0, 1}
		Meat	C6	{0, 1}
11	**The perceived percent of food thrown away monthly**		**FWP**	**{1, . . ., 6}**
12	"At the end of a meal, I throw away leftovers".		A1	{0, 1, 2}
13	"I freeze the leftovers from the meal and will eat them later or prepare other products from them".		A2	{0, 1, 2}
14	"The leftovers from the table are used in pet food".		A3	{0, 1, 2}
15	"I check the expiry date of the food at the time of purchase and will buy products with a longer shelf life".		A4	{0, 1, 2}
16	"I do selective recycling".		A5	{0, 1, 2}
17	Identified measures to reduce food waste		M	{1, . . ., 3}

The performance of the NNA will be established by referring to the following performance indicators:

- Performance on test data:
  - The accuracy: the proportion of the correct number of predictions.
  - The confusion matrix: a matrix that shows the number of correct and incorrect predictions of the model for each category.
  - The classification report, including precision, recall, and F1-Score, calculated based on the confusion matrix.
- Performance on training data, made on epochs:
  - The loss: a measure of error during training, determined using a categorical cross-entropy function of the type shown in Equation (2). The loss function penalizes wrong predictions based on the distance between the predicted value and the actual value
  - The accuracy: the proportion of the correct predictions made on the training data.

$$loss = -\sum_i y_i \log(\hat{y}_i),\ y_i = \text{the actual value, } (\hat{y}_i) = \text{the predicted value} \quad (2)$$

The model will be run for a specific number of times and the run with the best parameter will be presented, as well as the average values of the parameters for the number of runs.

2.2.2. Decision Tree Approach Methodology

The methodology used for the DT approach has approximately the same phases, with the different ones being established in the model-building step. Thus, the model consists of the development of a decision tree with a CART (Classification And Regression Tree) variation. The selection of the DT variation was based on the input data type.

The performance of the DTA will be established by referring to the following performance indicators, with the same meaning as presented for the NNA: accuracy, precision, recall, F1-Score, and the confusion matrix. Besides these, another two indicators are used:

- The ROC–AUC (Receiver Operating Characteristic—Area Under the Curve), used for evaluating classification models, especially when the classes are unbalanced. This measures the ability of the model to differentiate between positive and negative classes. If AUC is 1, the model makes perfect predictions, while a score of 0.5 is similar to random classification.
- The MCC (Matthew's Correlation Coefficient), used to evaluate the quality of the binary classification. If MCC is equal to 1, the model makes perfect predictions; at 0, it is similar to random classification, and at -1, the model makes predictions opposite to reality.

2.2.3. The Comparative Analysis

The two approaches have similar sequences of steps, with the main differences being the specific tools and data structure used for implementation. Also, the input data configuration is another important difference, with this aspect being considered among those studied in this research, in order to find the most suitable model for the current data configuration. The neural network, being a more complex model capable of capturing non-linear relationships between variables, requires a large amount of data for training and an intensive hyperparameter tuning process. In contrast, decision trees are simpler to implement and interpret but often suffer from overlearning and are limited in capturing complex relationships without additional techniques such as bagging or boosting.

2.3. Data Preprocessing

The data obtained in the questionnaire were preprocessed in order to fit the needs of the presented models. The preprocessing phase consisted of the following:

1. The separation of the data into independent (34 variables) and dependent (1 variable).
2. The encoding of the qualitative data as categorical; this is performed by transforming the answers into numerical categories. For unique-choice questions, the possible value set contains numbers from 1 to the number of choices, and for multiple-choice questions, each choice was encoded with 0 or 1, depending on its selection or not. These data are presented in Table 2.
3. The encoding of the categorical data obtained at the previous step; this is performed within the development of the models and transforms categorical data into numerical data due to its usage in the development of the structures (neural network or decision tree).
4. The normalization of the data, consisting of the standardization (data are scaled in order to obtain a mean of 0 and a standard deviation of 1). This is performed in order to ease the stabilization of the training process.
5. The split process, according to which the data are split into training and testing data, with a proportion of 80% and 20% of the data obtained at the previous step. Training data are used in the learning process of the models and testing data are used for the validation of the obtained results with the original results after the model is trained.

After this step, the obtained data are then used in the two models. The Neural Network Approach (NNA) was developed using Python-based implementation, using the sklearn and tensorflow libraries, commonly chosen for this type of implementation. These are well-suited to developing and training neural networks. The Python environment and its libraries were chosen for their robustness, extensive community support, and flexibility in handling complex machine learning tasks. The Decision Tree Approach (DTA) was developed using the Orange software (version 3.37.0). Orange is an open-source machine learning and data visualization software known for its user-friendly interface and powerful data analysis capabilities. Orange is particularly popular in this field for its ability to easily visualize and interpret decision tree models, making it an ideal choice for this aspect of the research.

An important observation is related to the presence of abnormalities or outliers in the data. These were included in the approaches used (DTA and NNA) by their default methodologies. Thus, we considered that the DT and NN approaches are adequate to deal with the presence of outliers automatically, without the need for specific additional intervention (e.g., the Decision Tree Approach presents successive decision criteria selection, which significantly lowers the impact of the outliers of the final results).

3. Results

The results were obtained for both approaches using the presented methodology. Each result aspect will be presented for each approach based on the performance of the model. The results are established based on the performance indicators mentioned for each approach and the testing data.

3.1. Results for NNA

3.1.1. Performance Results for NNA

The overall performance of the neural network with the best parameters established an accuracy level of 0.78, showing the relatively high precision of the prediction for the testing data (approximately 78% of the NN predictions are accurate). The MCC value is situated at 0.70, showing a robust model.

As for the average values, the number of runs in order to determine the average performance of the model was set to 10. The overall performance of the neural network with the average parameters established an accuracy level of 0.69, showing relatively high precision of the prediction for the testing data (approximately 70% of the NN predictions are accurate). The MCC value is situated at 0.57, showing a moderate performance model.

Next, the confusion matrix shows the correct predictions across the six classes for the testing data (20% of the total dataset volume). The six classes correspond to the six responses to the question "The perceived percent of food thrown away monthly", which was considered the dependent variable, encoded as 1 to 6. The confusion matrix is shown in Table 2, showing data from both the best performance and the average performance (each cell contains "best/average" performance).

The interpretation of the confusion matrix is related to the correct prediction for each class. Thus, the prediction performance for the data clustered in each class has the following configuration related to the best performance values:

- For Class 1, shown in row 1, 26 answers were correctly classified (the predicted class was the same as the existent class) and 1 was incorrectly classified as being part of Class 2.
- For Class 2, 8 answers were correctly classified and 9 incorrectly (4 for Class 1 and 5 for Class 3).
- For Class 3, 23 answers were correctly classified and 0 were incorrectly classified.
- For Class 4, 0 answers were correctly classified and 5 were incorrectly classified as Class 3.
- For Class 5, 0 answers were correctly classified and 1 was incorrectly classified as Class 3.
- For Class 6, no data existed in the testing or training datasets.

For a better overview of the performance, the classification report was generated and is shown in Table 3, both for the best and average performances.

Table 3. The classification report of the NN Approach, containing precision, recall, and F1-Score indicators.

Class	Precision	Recall	F1-Score	Support
1	0.87/0.82	0.96/0.89	0.91/0.85	27/27
2	0.89/0.55	0.47/0.36	0.62/0.43	17/17
3	0.68/0.64	1.00/0.88	0.81/0.74	23/23
4	0.00/0.00	0.00/0.00	0.00/0.00	5/5
5	0.00/0.00	0.00/0.00	0.00/0.00	1/1
6	0.00/0.00	0.00/0.00	0.00/0.00	0/0

The indicators from the classification report show the performance of the model regarding classes in a clearer manner. In this matter:

- Related to precision, relatively high values are established for Class 1 and Class 3. For Class 1, 87% of the answers predicted to be from Class 1 were correct, and for Class 2, this value was 89%. For Class 3, the precision was moderate.
- Related to recall, higher values are also found for Class 1 and Class 3, meaning that 96% and 100% of the real answers are correctly identified by the model, respectively.
- For the F1-Score, the results confirm the good balance between the precision and the recall for Classes 1 and 3 (91% and 81%).
- The support shows the number of real answers given by the respondents classified across the six classes.

The model performs better for Classes 1 and 3, with moderate performance for Class 2 and low performance for Class 4. This indicates that Class 4 is more complex or has an unbalanced data distribution, leading to the conclusion that the model would need better data distribution or hyperparameter optimization.

Compared to the testing indicators showing the quality of the model's prediction using new data, the performance indicators related to the training phase (epochs, accuracy, and loss) show the way the model improves over time. The set of epochs was established as 11 in order to avoid overfitting. The best and average values of the indicators are shown in Table 4.

Table 4. The training performance indicators for the NN Approach.

Epoch	Number of Batches	Time Per Step (ms)	Accuracy	Loss
Epoch 1	10/10	2	0.3218/0.2767	1.6476/1.7075
Epoch 2	10/10	3	0.5249/0.5140	1.2643/1.3178
Epoch 3	10/10	4	0.6412/0.6120	1.0681/1.1276
Epoch 4	10/10	4	0.7219/0.6551	0.9196/0.9965
Epoch 5	10/10	3	0.7483/0.7065	0.8270/0.8880
Epoch 6	10/10	4	0.7704/0.7401	0.7548/0.7967
Epoch 7	10/10	3	0.7770/0.7699	0.6849/0.7145
Epoch 8	10/10	3	0.8264/0.7993	0.5643/0.6397
Epoch 9	10/10	3	0.8745/0.8404	0.5141/0.5727
Epoch 10	10/10	2	0.8914/0.8709	0.4554/0.5134
Epoch 11	10/10	2	0.8728/0.8918	0.4398/0.4561
Testing	3/3	10	0.8104	0.6593

We can observe that the training data were split into 10 batches, with 11 epochs (iterations) through the training data. The time statistic was a performant one, with typical time values for processing the data batches. Regarding accuracy, the value for Epoch 1 shows a low accuracy that grows over time, reaching over 87% in the final epoch. Thus, the final accuracy for the training data was set to 87.28%, compared to 81.04% for the testing data. As for the loss, the function shows a progressive decrease, reaching 43.98% for the training data and 65.93% for the testing data. The higher value for the testing data than for the training data may indicate potential overfitting but within limits. For a higher degree of confirmation of the results, we present the ROC curves for each class of the present model in Figure 6. The ROC (Receiver Operating Characteristic) plot gives us a confirmation evaluation of the performance of the multi-class classification model. In the ROC plot, each curve in the graph corresponds to a specific class and reflects the model's ability to distinguish that class from the others. The closer a curve is to the upper left corner of the graph, the more effective the model is at correctly classifying specimens in that class.

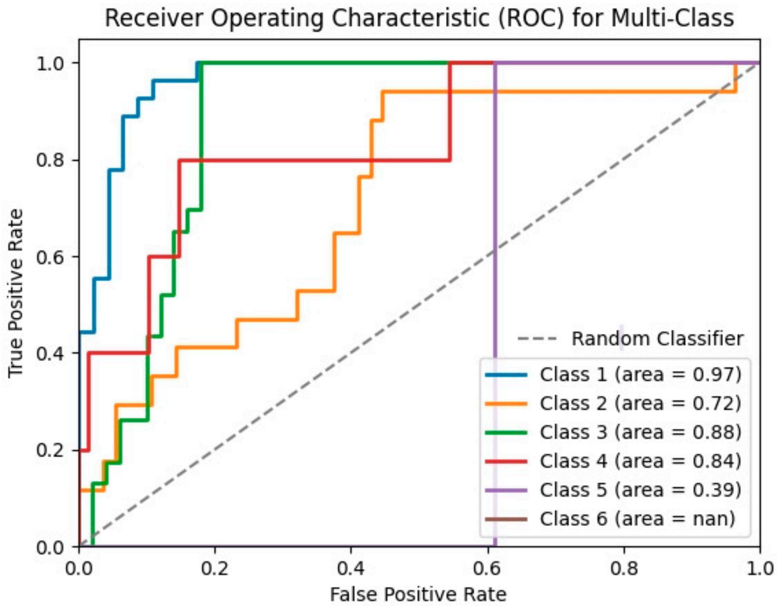


Figure 6. The ROC curves for multi-class analysis for the six classes for NN Approach (multi-run results).

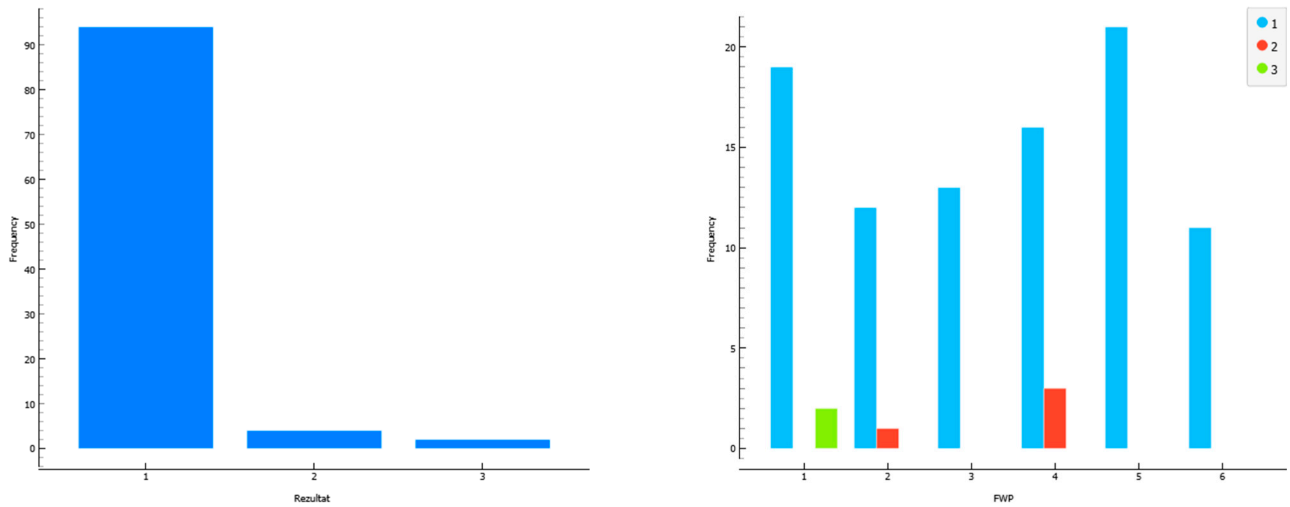
Analyzing the class performance shown in Figure 6, it is observed that the model behaves excellently in the case of Classes 1 (blue) and 3 (green), with AUC values close to 1, which suggests a very accurate classification of specimens in these classes. Classes 2 and 4 have AUC values around 0.8, indicating solid performance but with potential for improvement. In contrast, Class 5 presents an AUC value of 0.39, reflecting significant difficulties in classification. Class 6, on the other hand, has an AUC value of "nan" (not a number), due to insufficient data.

Related to the prediction results, the Neural Network Approach (NNA) shows a solid performance in its predictions, especially for classes that represent lower proportions of food waste. Class 1 was ranked correctly in most cases, both in the best-case scenario and in the average performance. This suggests that the model can make accurate predictions for segments that contribute less to food waste, providing a useful tool for identifying those consumers or products where waste is minimal and can be effectively managed. In contrast, the model has significant difficulty in correctly classifying observations in Classes 5 and 6, which represent higher proportions of food waste. These classes are underrepresented in the confusion matrix, indicating low reliability of predictions for segments that generate significant food waste.

In summary, we can determine that the NN model presented above shows a decent performance, reflected in the high proportion of correct predictions for the testing data. In this matter, the model can be considered reliable for the prediction of new data.

3.1.2. Prediction Data Results for NNA

Data results were obtained by applying the model to 100 new entries in a dataset. The dataset for the prediction data results was generated randomly, thus the expected performance indicators were low in comparison to human-generated data. The descriptive statistics related to the class distribution of these 100 responses are shown in Figure 7.



(**a**) (**b**)

Figure 7. The distribution of the classes related to the new dataset for the NN Approach: (**a**) the distribution of predicted classes; (**b**) the distribution of predicted classes compared to the real (randomly generated) classes.

The graphically presented data show the distribution of the classes predicted by the model. The first graphic shows the general distribution of the predicted classes, while the second graphic shows a grouped distribution of predicted classes as compared to the initial classes included in the dataset. More specifically, the second graph shows the number of predicted instances that match the real (randomly generated) instance. In the case of perfect prediction, the two graphs should have similar distributions. The distribution configuration shows that the model is well-trained to identify the classes, with a decent behavior related to randomly generated data, as shown in the second graph. The measured accuracy was determined to be around 23%, compared to a theoretical threshold of 16%, measured according to the number of classes and the probability of each entry being in a specific class.

3.2. Results for DTA

3.2.1. Performance Results for DTA

The results for the Decision Tree Approach present the main performance indicators shown in the methodology. The final accuracy was determined to be 31.5%, showing a low level of prediction accuracy. Furthermore, the MCC was determined to be −0.028 and the ROC–AUC to 0.465. Thus, the model performs poorly, with the results being close to random guessing. The confusion matrix is shown in Table 5.

Table 5. The confusion matrix of the DT Approach.

	1	**2**	**3**	**4**	**5**	**6**
1	15	2	9	1	0	0
2	11	0	6	0	0	0
3	12	3	8	0	0	0
4	2	0	3	0	0	0
5	0	0	0	1	0	0
6	0	0	0	0	0	0

The interpretation of the confusion matrix is related to the correct prediction for each class. Thus, the prediction performance on the data clustered in each class has the following configuration related to the best performance values:

- Performance for Class 1: the model performs relatively well for Class 1, with 15 correctly classified instances and a moderate number of confusions with other classes.
- Performance for Class 2: the model fails to correctly classify any instance in Class 2. All instances in this class are confounded with other classes, especially Class 1 and Class 3.
- Performance for Class 3: the model makes some correct classifications for Class 3, but there are many instances confused with Class 1 and Class 2.
- Performance for Class 4: instances of Class 4 are never correctly predicted. Instances of this class are confused with Classes 1 and 3.
- Performance for Class 5: the model has limited performance for Class 5, with only one instance correctly classified and one misclassified as Class 4.
- Performance for Class 6: Class 6 is not represented correctly in the test dataset. This can be caused by missing data or a problem with the model.

These results suggest that the model has significant difficulties in recognizing and differentiating certain classes. To improve performance, one should check the balance and representativeness of the data, adjust the model hyperparameters, explore other models, and examine the relevance of the features used. Regarding prediction reliability, the Decision Tree Approach shows significant limitations in its ability to correctly classify observations based on the proportions of food waste. In particular, the model faces major difficulties in correctly identifying cases that fall into classes with intermediate and high proportions of food waste (Classes 3, 4, 5, and 6). This suggests that in future predictions, the model may make notable errors, especially in scenarios involving higher wastage categories. In addition, the results of the conclusion report are shown in Table 6.

Table 6. The classification report of the DT Approach, containing precision, recall, and F1-Score indicators.

Class	Precision	Recall	F1-Score	Support
1	0.375	0.556	0.448	27
2	0.000	0.000	0.000	17
3	0.308	0.348	0.327	23
4	0.000	0.000	0.000	5
5	0.000	0.000	0.000	1
6	0.000	0.000	0.000	0

Analyzing the performance of the model based on the precision, recall, and F1-Score methods, it is observed that the model presents significant difficulties in classifying most of the classes. Class 1 is the only one for which the model achieves relatively better results, with a precision of 0.375 and a recall of 0.556. However, for Classes 2, 4, 5, and 6, the model fails to correctly predict any instance, with values of 0 for all performance measures. Class 3 performs modestly, with a precision of 0.308 and a recall of 0.348. The obtained tree is represented visually in Figure 8.

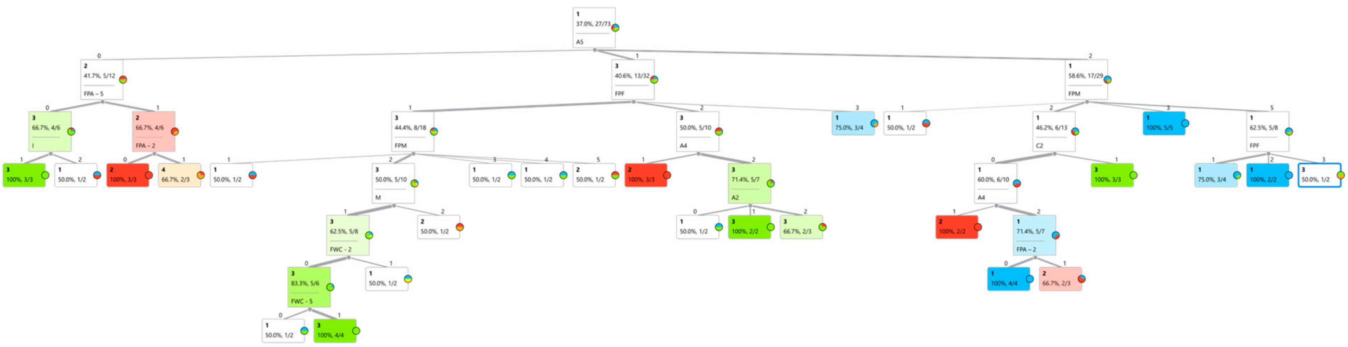


Figure 8. The visual representation of the DT Approach.

Figure 8 shows a graphic representation of the decision tree, where the leaf nodes represent the final classification results in visual form. Blue nodes represent Class 1, red nodes represent Class 2, and green nodes represent Class 3.

The ROC curves for the DT Approach, with the same significance as those presented in Figure 6 for the NNA, are presented in Figure 9.

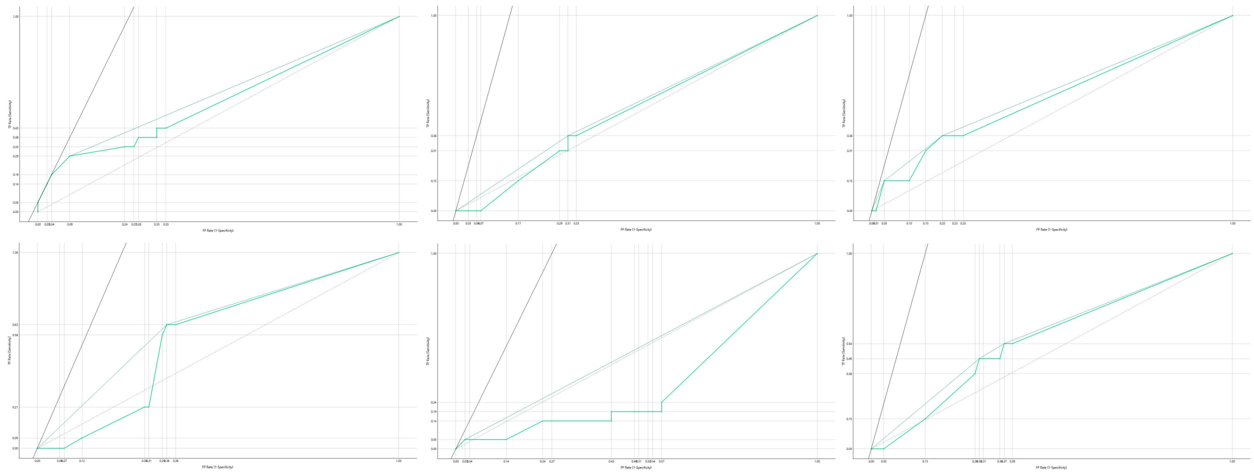


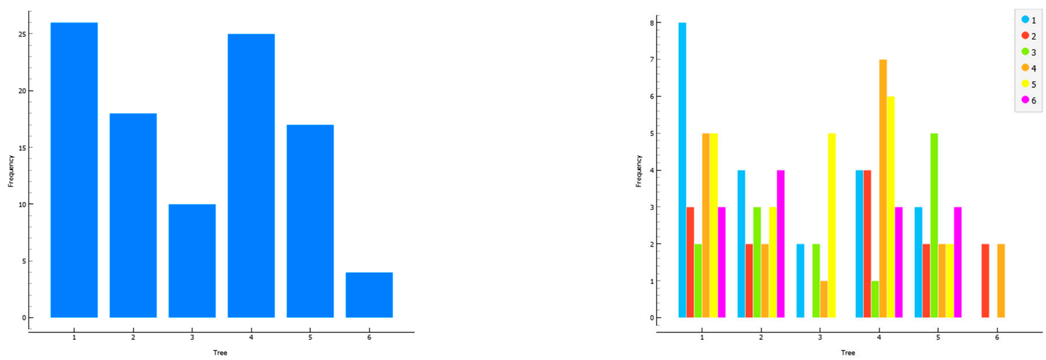
Figure 9. The ROC curves for multi-class analysis for the six classes for DT Approach.

In Figure 9, the ROC curves for the DT Approach confirm the performance of the DT-based prediction model shown by the classification report, establishing that the predictions are slightly more accurate for Class 1, with those for the rest of the classes being close to random prediction (the ROC curves are almost identical to the diagonal from [0] to [1], determined by random prediction). The diagonal dashed line shows the random classifier, the vertical lines correspondent to each point represents the FPR (False Positive Rate) in the respective point, while the horizontal lines correspondent to each point represents the TPR (True Positive Rate) in that respective point.

Overall, these results suggest that the model requires considerable improvement, either by tuning the hyperparameters or by exploring other machine learning techniques. It is also essential to check the balance and representativeness of the data, ensuring that each class is well-represented in the training and test sets.

3.2.2. Prediction Data Results for DTA

For the same subset generated for the NNA approach, the DTA model was applied to the same data. The results are shown in Figure 10.



(**a**) (**b**)

Figure 10. The distribution of the classes related to the new dataset for the DT Approach: (**a**) the distribution of predicted classes; (**b**) the distribution of predicted classes compared to the real (randomly generated) classes.

The same distribution configuration was generated as in the case of the NN Approach. The class distribution is more balanced, but less accurate, due to the poor values of the DTA performance indicators. The second graph also shows the distribution of real instances for each predicted class. In the case of perfect prediction, the two graphs should have similar distributions. Regarding the comparison with a randomly generated dependent variable, the accuracy was determined to be 21%, the ROC-AUC was 0.514, and the MCC was 0.038, representing a good limit compared to an accuracy of 16% but presenting a model that does not provide a robust set of results.

4. Discussion

The prediction models related to FW are used to prevent large quantities of food waste in various contexts. The data that can be used to generate predictions related to FW can have various forms in the context of using neural networks (e.g., statistical data, image-based data [81]). As for the decision tree models, similar research studies [82] analyzed the performance of the prediction model using statistical indicators (e.g., correlation coefficient, root square means error, etc.). This approach will be followed, as mentioned previously, in future research studies related to FLW. Also, an extended comparison of several machine learning methods for FW prediction made in [83] showed a relatively high performance of a DT model (an accuracy of 0.75) in the context of an ensemble of machine learning methods (e.g., random forest, logistic regression, Support Vector Machine, Gaussian Naïve Bayes, and AdaBoost).

In our study, the neural network demonstrated superior performance compared to decision trees. In the confusion matrix analysis, the neural network was able to make correct predictions for most classes with an overall accuracy of 78%. This suggests that the neural network is effective in correctly identifying and classifying test instances. Indicatively, the MCC (Matthews Correlation Coefficient) value of 0.70 reflects a significant positive correlation between predicted and actual values, indicating a robust and reliable model.

In contrast, decision trees performed more poorly. The confusion matrix for the decision trees shows that most of the predictions are wrong and the number of correctly classified instances is relatively small. The overall accuracy of the decision tree model was only 31.5%, indicating poor performance. The MCC value of −0.028 suggests that the model has a negative correlation between its predictions and the actual values, approaching random guessing. Also, the ROC–AUC of 0.465 underlines the model's difficulty in effectively separating the classes, indicating near-random performance.

Thus, the neural network proved to be much more efficient and reliable than decision trees for this specific classification task and dataset configuration, providing more accurate predictions and better correlation between predicted and actual results. The ability of the NNA to generalize across diverse consumer segments emphasizes its robustness, particularly in the presence of noise and outliers. In contrast, the Decision Tree Approach, while easier to interpret, suffered from overfitting, resulting in lower predictive accuracy.

As for the socio-economic indicators, several conclusions can be drawn. The impact of socio-economic variables on food waste, according to the NN and DT results, shows that these 34 variables have a great combined impact from a socio-economic point of view, with emphasis related to the influence of demographic and economic data on final predictions. Further research must be developed in order to determine the univariate influence of key variables on the final prediction in a quantitative manner, thus providing a clearer picture related to each variable's influence on the final result.

The main aspects that may be improved in both approaches are related to:

- The dataset configuration and volume, which must have a more balanced distribution between classes and a larger volume, with data related to each class. For example, the dataset used in this paper lacks data for Class 6.
- The collection of data in various timeframes (surpassing the cross-sectional aspect of the data), which will lead to a greater robustness of the prediction model.

- The hyperparameter choice, such as grid search or random search, to find the best values for the model's hyperparameters. Thus, they may be tuned for better performances.
- The existence of a dataset used for prediction purposes, with the one used in this paper being generated randomly and, thus, leading to lower performances on data prediction for new instances.
- Data preprocessing, related to a better normalization, standardization, or dimensionality reduction.

Also, this analysis was conducted in order to confirm the first hypothesis (H1) stated in Section 1 (Introduction) referring to relatively high levels of accuracy of prediction models based on machine learning methods. Also, the second hypothesis (H2) was partially confirmed, especially for the current dataset, leading to the conclusion that both approaches are suitable for an FW prediction model according to the methodology and necessary resources. However, the lower performance of the DT Approach showed that the most suitable approach for the current analysis was the NN Approach, confirming the third hypothesis (H3) stated in the Introduction.

By applying the NN model's predictions in real-world scenarios, policymakers and businesses can more effectively design and implement strategies to mitigate food waste. Furthermore, the findings provide a foundation for future research aimed at refining predictive models and enhancing their applicability in diverse contexts.

5. Conclusions

Comparing the performances of neural networks and decision trees, it can be concluded that neural networks are much more efficient for the classification task at hand. With an accuracy of 78%, the neural network demonstrates a robust ability to make correct predictions, also reflected by the MCC value of 0.70, indicating a strong correlation between predictions and actual values. These results show that the neural network can be considered a reliable model for this specific application.

The results show that the neural network outperformed decision trees in accuracy and robustness, suggesting that the complex methodology and generalization ability of neural networks are more suitable for this specific task, despite the need for higher computational resources and optimization efforts.

Other important findings show that socio-economic factors determine and influence food loss and waste dynamics and quantities. In this matter, future work will include a quantitative determination of these influences on food loss and waste.

Important future directions of work related to this research include a comparison of results obtained by machine learning methods with results obtained using other prediction methods (e.g., statistical and econometric methods, pattern recognition methods, etc.). This will emphasize the situations in which the two categories of methods should be used, also taking into account the specific objective of a research study that would use a specific category of methods.

At present, the model shows a decent performance related to training and testing data, as well as new data used for prediction. However, the models render specific limitations, mostly related to dataset structure and volume. These limitations, in addition to improvements in the model parameters and methodology, represent a future direction of development of the research on the food loss and waste phenomenon.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agriculture14101837/s1, Survey.

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References

1. Spang, E.S.; Moreno, L.C.; Pace, S.A.; Achmon, Y.; Donis-Gonzalez, I.; Gosliner, W.A.; Jablonski-Sheffield, M.P.; Momin, M.A.; Quested, T.E.; Winans, K.S.; et al. Food Loss and Waste: Measurement, Drivers, and Solutions. *Annu. Rev. Environ. Resour.* **2019**, *44*, 117–156. [CrossRef]
2. Horton, P.; Bruce, R.; Reynolds, C.; Milligan, G. Food Chain Inefficiency (FCI): Accounting Conversion Efficiencies Across Entire Food Supply Chains to Re-define Food Loss and Waste. *Front. Sustain. Food Syst.* **2019**, *3*, 79. [CrossRef]
3. Ishangulyyev, R.; Sanghyo, K.; Sang, H.L. Understanding Food Loss and Waste—Why Are We Losing and Wasting Food? *Foods* **2019**, *8*, 297. [CrossRef] [PubMed]
4. Luo, N.; Olsen, T.; Liu, Y.; Zhang, A. Reducing food loss and waste in supply chain operations. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *162*, 102730. [CrossRef]
5. Kör, B.; Krawczyk, A.; Wakkee, I. Addressing food loss and waste prevention, *Br. Food J.* **2022**, *124*, 2434–2460. [CrossRef]
6. Xue, L.; Liu, G.; Parfitt, J.; Liu, X.; Van Herpen, E.; Stenmarck, Å.; O'Connor, C.; Östergren, K.; Cheng, S. Missing Food, Missing Data? A Critical Review of Global Food Losses and Food Waste Data. *Environ. Sci. Technol.* **2017**, *51*, 6618–6633. [CrossRef] [PubMed]
7. Parfitt, J.; Barthel, M.; Macnaughton, S. Food Waste within Food Supply Chains: Quantification and Potential for Change to 2050. *Philos. Trans. R. Soc. B Biol. Sci.* **2010**, *365*, 3065–3081. [CrossRef]
8. Wang, Y.; Yuan, Z.; Tang, Y. Enhancing Food Security and Environmental Sustainability: A Critical Review of Food Loss and Waste Management. *Resour. Environ. Sustain.* **2021**, *4*, 100023. [CrossRef]
9. De, B.; Hussain, I.; Das, R.C. Environmental Implications of Food Waste: A Study on South-Asian Countries. In *Renewable Energy Investments for Sustainable Business Projects*; Dinçer, H., Yüksel, S., Eds.; Emerald Publishing Limited: Leeds, UK, 2023; pp. 45–58. [CrossRef]
10. Omolayo, Y.; Feingold, B.J.; Neff, R.A.; Xue, X. Life Cycle Assessment of Food Loss and Waste in the Food Supply Chain. *Resour. Conserv. Recycl.* **2021**, *164*, 105119. [CrossRef]
11. Martins de Oliveira, M.; Lago, A.; Dal'Magro, G.P. Food Loss and Waste in the Context of the Circular Economy: A Systematic Review. *J. Clean. Prod.* **2021**, *294*, 126284. [CrossRef]
12. Magalhães, V.S.M.; Ferreira, L.M.D.F.; Silva, C. Causes and Mitigation Strategies of Food Loss and Waste: A Systematic Literature Review and Framework Development. *Sustain. Prod. Consum.* **2021**, *28*, 1580–1599. [CrossRef]
13. Cattaneo, A.; Sánchez, M.V.; Torero, M.; Vos, R. Reducing Food Loss and Waste: Five Challenges for Policy and Research. *Food Policy* **2021**, *98*, 101974. [CrossRef] [PubMed]
14. Santeramo, F.G.; Lamonaca, E. Food Loss–Food Waste–Food Security: A New Research Agenda. *Sustainability* **2021**, *13*, 4642. [CrossRef]
15. Derqui, B.; Fayos, T.; Fernandez, V. Towards a More Sustainable Food Supply Chain: Opening up Invisible Waste in Food Service. *Sustainability* **2016**, *8*, 693. [CrossRef]
16. Chauhan, C.; Dhir, A.; Ul Akram, M.; Salo, J. Food Loss and Waste in Food Supply Chains: A Systematic Literature Review and Framework Development Approach. *J. Clean. Prod.* **2021**, *295*, 126438. [CrossRef]
17. Ioannou, T.; Bazigou, K.; Katsigianni, A.; Fotiadis, M.; Chroni, C.; Manios, T.; Daliakopoulos, I.; Tsompanidis, C.; Michalodimitraki, E.; Lasaridi, K. The "A2UFood Training Kit": Participatory Workshops to Minimize Food Loss and Waste. *Sustainability* **2022**, *14*, 2446. [CrossRef]
18. Luo, N.; Olsen, T.L.; Liu, Y. A Conceptual Framework to Analyze Food Loss and Waste within Food Supply Chains: An Operations Management Perspective. *Sustainability* **2021**, *13*, 927–945. [CrossRef]
19. Caputo, P.; Ducoli, C.; Clementi, M. Strategies and Tools for Eco-Efficient Local Food Supply Scenarios. *Sustainability* **2014**, *6*, 631–651. [CrossRef]

20. Wikström, F.; Verghese, K.; Auras, R.; Olsson, A.; Williams, H.; Wever, R.; Soukka, R. Packaging Strategies that Save Food: A Research Agenda for 2030. *J. Ind. Ecol.* **2019**, *23*, 532–540. [CrossRef]
21. Trevisan, C.; Formentini, M. Digital Technologies for Food Loss and Waste Prevention and Reduction in Agri-Food Supply Chains: A Systematic Literature Review and Research Agenda. *IEEE Trans. Eng. Manag.* **2023**, *71*, 12326–12345. [CrossRef]
22. Birisci, E.; McGarvey, R.G. Optimal Production Planning Utilizing Leftovers for an All-You-Care-to-Eat Food Service Operation. *J. Clean. Prod.* **2018**, *171*, 984–994. [CrossRef]
23. Blakeney, M. Strategies for FLW Reduction. In *Food Loss and Food Waste*; Edward Elgar Publishing: Cheltenham, UK, 2019; pp. 138–178.
24. Peira, G.; Bollani, L.; Giachino, C.; Bonadonna, A. The Management of Unsold Food in Outdoor Market Areas: Food Operators' Behaviour and Attitudes. *Sustainability* **2018**, *10*, 1180. [CrossRef]
25. Bucatariu, C. Recovery and Redistribution of Safe and Nutritious Food for Human Consumption and Food Waste Prevention and Reduction. In *Knowledge and Information for Sustainable Food Systems*; FAO: Rome, Italy, 2014; pp. 133–150.
26. De Clercq, D.; Wen, Z.; Gottfried, O.; Schmidt, F.; Fei, F. A Review of Global Strategies Promoting the Conversion of Food Waste to Bioenergy via Anaerobic Digestion. *Renew. Sustain. Energy Rev.* **2017**, *79*, 204–221. [CrossRef]
27. Santeramo, F.G.; Carlucci, D.; De Devitiis, B.; Seccia, A.; Stasi, A.; Viscecchia, R.; Nardone, G. Emerging Trends in European Food, Diets and Food Industry. *Food Res. Int.* **2018**, *104*, 39–47. [CrossRef] [PubMed]
28. Pocol, C.B.; Pinoteau, M.; Amuza, A.; Burlea-Schiopoiu, A.; Glogovețan, A.-I. Food Waste Behavior among Romanian Consumers: A Cluster Analysis. *Sustainability* **2020**, *12*, 9708. [CrossRef]
29. Survey. Available online: https://forms.gle/j1D7c1ExiyioQNBSA (accessed on 31 July 2024).
30. Pan, S.; Duraisamy, K. Long-Time Predictive Modeling of Nonlinear Dynamical Systems Using Neural Networks. *Complexity* **2018**, *1*, 4801012. [CrossRef]
31. Philip Plumb, A.; Rowe, R.C.; York, P.; Brown, M. Optimisation of the predictive ability of artificial neural network (ANN) models: A comparison of three ANN programs and four classes of training algorithm. *Eur. J. Pharm. Sci.* **2005**, *25*, 395–405. [CrossRef]
32. McCarthy, R.V.; McCarthy, M.M.; Ceccucci, W.; Halawi, L. Predictive Models Using Decision Trees. In *Applying Predictive Analytics: Finding Value in Data*; Springer International Publishing: Cham, Switzerland, 2019; pp. 123–144. [CrossRef]
33. Rodrigues, M.; Miguéis, V.; Freitas, S.; Machado, T. Machine Learning Models for Short-Term Demand Forecasting in Food Catering Services: A Solution to Reduce Food Waste. *J. Clean. Prod.* **2024**, *435*, 140265. [CrossRef]
34. Panda, S.K.; Dwivedi, M. Minimizing Food Wastage Using Machine Learning: A Novel Approach. In *Smart Intelligent Computing and Applications: Proceedings of the Third International Conference on Smart Computing and Informatics*; Springer: Singapore, 2020; Volume 1, pp. 123–132.
35. Ozcil, I.E. Reducing Food Waste Using Machine Learning Models: Forecasting and Optimization Approaches. *J. Data Sci. Artif. Intell.* **2024**, *2*, 000136. [CrossRef]
36. Malefors, C.; Secondi, L.; Marchetti, S.; Eriksson, M. Food Waste Reduction and Economic Savings in Times of Crisis: The Potential of Machine Learning Methods to Plan Guest Attendance in Swedish Public Catering during the COVID-19 Pandemic. *Socio-Econ. Plan. Sci.* **2022**, *82*, 101041. [CrossRef]
37. Brandić, I.; Pezo, L.; Žlabur, J.Š.; Peter, A.; Šurić, J.; Voća, N. Application of Artificial Neural Network Models to Predict Food Waste in the European Union. In Proceedings of the 58th Croatian & 18th International Symposium on Agriculture, Dubrovnik, Croatia, 11–17 February 2023; pp. 416–421.
38. Aci, M.; Yergök, D. Demand Forecasting for Food Production Using Machine Learning Algorithms: A Case Study of University Refectory. *Teh. Vjesn.* **2023**, *30*, 1683–1691.
39. Solano Meza, J.K.; Orjuela Yepes, D.; Rodrigo-Ilarri, J.; Cassiraga, E. Predictive Analysis of Urban Waste Generation for the City of Bogotá, Colombia, Through the Implementation of Decision Trees-Based Machine Learning, Support Vector Machines, and Artificial Neural Networks. *Heliyon* **2019**, *5*, e02810. [CrossRef] [PubMed]
40. Singh, B.; Kaunert, C. Salvaging Responsible Consumption and Production of Food in the Hospitality Industry: Harnessing Machine Learning and Deep Learning for Zero Food Waste. In *Sustainable Disposal Methods of Food Wastes in Hospitality Operations*; IGI Global: Hershey, PA, USA, 2024; pp. 176–192.
41. Onyeaka, H.; Tamasiga, P.; Nwauzoma, U.M.; Miri, T.; Nwaiwu, O.; Akinsemolu, A.A. Using Artificial Intelligence to Tackle Food Waste and Enhance the Circular Economy: Maximising Resource Efficiency and Minimising Environmental Impact: A Review. *Sustainability* **2023**, *15*, 10482. [CrossRef]
42. Chen, W.-S.; Yin-Kuan, D. Using neural networks and data mining techniques for the financial distress prediction model. *Expert Syst. Appl.* **2009**, *36*, 4075–4086. [CrossRef]
43. Broby, D. The use of predictive analytics in finance. *J. Financ. Data Sci.* **2022**, *8*, 145–161. [CrossRef]
44. Yang, C.C. Explainable artificial intelligence for predictive modeling in healthcare. *J. Healthc. Inform. Res.* **2022**, *6*, 228–239. [CrossRef]
45. Stiglic, G.; Kocbek, P.; Fijacko, N.; Zitnik, M.; Verbert, K.; Cilar, L. Interpretability of machine learning-based prediction models in healthcare. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2020**, *10*, e1379. [CrossRef]
46. Chandadevi, G.; Johansson, U.; Löfström, T. Predictive Modeling of Campaigns to Quantify Performance in Fashion Retail Industry. In Proceedings of the IEEE International Conference on Big Data (Big Data), Los Angeles, CA, USA, 9–12 December 2019.

47. Güner, M.; Retail Data Predictive Analysis Using Machine Learning Models. MEF Üniversitesi Fen Bilim. *Enstitüsü Bilişim Teknol. Yüksek Lisans Programı*. 2021, pp. 1–39. Available online: https://hdl.handle.net/20.500.11779/1686 (accessed on 31 July 2024).
48. Bradlow, E.T.; Gangwar, M.; Kopalle, P.; Voleti, S. The Role of Big Data and Predictive Analytics in Retailing. *J. Retail.* **2017**, *93*, 79–95. [CrossRef]
49. Seyedan, M.; Mafakheri, F. Predictive big data analytics for supply chain demand forecasting: Methods, applications, and research opportunities. *J. Big Data* **2020**, *7*, 53. [CrossRef]
50. Oyewole, A.T.; Okoye, C.C.; Ofodile, O.C.; Ejairu, E. Reviewing predictive analytics in supply chain management: Applications and benefits. *World J. Adv. Res. Rev.* **2024**, *21*, 568–574. [CrossRef]
51. Aljohani, A. Predictive Analytics and Machine Learning for Real-Time Supply Chain Risk Mitigation and Agility. *Sustainability* **2023**, *15*, 15008. [CrossRef]
52. Jaseena, K.U.; Kovoor, B.C. Deterministic weather forecasting models based on intelligent predictors: A survey. *J. King Saud Univ. Comput. Inf. Sci.* **2022**, *34*, 3393–3412. [CrossRef]
53. Weyn, J.A.; Durran, D.R.; Caruana, R.; Cresswell-Clay, N. Sub-seasonal forecasting with a large ensemble of deep-learning weather prediction models. *J. Adv. Model. Earth Syst.* **2021**, *13*, e2021MS002502. [CrossRef]
54. Segarra, L.; Hu Du, E.; Ruiz, G.R.; Bandera, C.F. Methodology for the Quantification of the Impact of Weather Forecasts in Predictive Simulation Models. *Energies* **2019**, *12*, 1309. [CrossRef]
55. Sathiyaraj, R.; Bharathi, A.; Balusamy, B. *Advanced Intelligent Predictive Models for Urban Transportation*, 1st ed.; Chapman and Hall/CRC: New York, NY, USA, 2022. [CrossRef]
56. Iovan, Ș. Predictive analytics for transportation industry. *J. Inf. Syst. Oper. Manag.* **2017**, *11*, 58–71.
57. Zulkifli, F.; Zulkifley, M.; Nor, A.A. Systematic research on predictive models on students' academic performance in higher education. *Int. J. Recent Technol. Eng.* **2019**, *8*, 357–363.
58. Musso, M.F.; Cascallar, E.C.; Bostani, N.; Crawford, M. Identifying Reliable Predictors of Educational Outcomes Through Machine-Learning Predictive Modeling. *Front. Educ.* **2020**, *5*, 104. [CrossRef]
59. Hung, J.-L.; Shelton, B.E.; Yang, J.; Du, X. Improving Predictive Modeling for At-Risk Student Identification: A Multistage Approach. *IEEE Trans. Learn. Technol.* **2019**, *12*, 148–157. [CrossRef]
60. Schanes, K.; Dobernig, K.; Gözet, B. Food waste matters—A systematic review of household food waste practices and their policy implications. *J. Clean. Prod.* **2018**, *182*, 978–991. [CrossRef]
61. Stefan, V.; van Herpen, E.; Tudoran, A.A.; Lähteenmäki, L. Avoiding food waste by Romanian consumers: The importance of planning and shopping routines. *Food Qual. Prefer.* **2013**, *28*, 375–381. [CrossRef]
62. Chereji, A.-I.; Chiurciu, I.-A.; Popa, A.; Chereji, I.; Iorga, A.-M. Consumer Behaviour Regarding Food Waste in Romania, Rural versus Urban. *Agronomy* **2023**, *13*, 571. [CrossRef]
63. Chereji, A.I.; Beleiu, A.M.; Suiugan, D. Non-compliant aspects in supermarkets from the perspective of consumer protection. *Gen. Elem. Ann. Univ. Oradea Fascicle Ecotoxicol. Anim. Husb. Food Sci. Technol.* **2022**, *21*, 97.
64. Morna, A.A.; Brata, A.M.; Tirpe, O.P.; Muresan, I.C.; Arion, F.H.; Fora, A.F.; Popa, D.; Chereji, A.I.; Milin, I.A.; Bacter, R.V. Analysis of the factors and barriers influencing the consumption of organic products. Case of Bihor county, Romania. *Sci. Pap. Ser. Manag. Econ. Eng. Agric. Rural. Dev.* **2023**, *23*.
65. Carlsson, A. Predictive Regression Model Evaluation: Evaluating Predictive Machine Learning Models to Reduce Food Waste in the Dairy Industry. Master's Thesis, School of Electrical Engineering and Computer Science, Stockholm, Sweden, 2023. Available online: https://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-338359 (accessed on 1 August 2024).
66. Graham-Rowe, E.; Jessop, D.C.; Sparks, P. Predicting household food waste reduction using an extended theory of planned behaviour. *Resour. Conserv. Recycl.* **2015**, *101*, 194–202. [CrossRef]
67. Gui, J.; Li, Z.; Deng, X.; Yang, J.; Chen, D.; Li, W. An Analysis of Spatiotemporal Patterns in Chinese Agricultural Productivity Between 2004 and 2014. *Ecol. Indic.* **2019**, *105*, 591–600. [CrossRef]
68. Arunraj, N.S.; Ahrens, D.; Fernandes, M.; Müller, M. Time Series Sales Forecasting to Reduce Food Waste in Retail Industry. In Proceedings of the 34th International Symposium on Forecasting, Rotterdam, The Netherlands, 29 June–2 July 2014.
69. He, D.; Deng, X.; Wang, X.; Zhang, F. Livestock Greenhouse Gas Emission and Mitigation Potential in China. *J. Environ. Manag.* **2023**, *348*, 119494. [CrossRef] [PubMed]
70. Smedescu, C.; Smedescu, D.; Mărcuță, A.; Mărcuță, L.; Tudor, V.C. From soil to table: Evaluating conventional and ecological cultivation systems in South-West Oltenia, Romania. *Sci. Pap. Ser. Manag. Econ. Eng. Agric. Rural. Dev.* **2023**, *23*, 821–829.
71. Smedescu, C.; Micu, M.M.; Tudor, V.C. Farm size and specialization structure in the European countries in the year 2020. *Sci. Pap. Ser. Manag. Econ. Eng. Agric. Rural. Dev.* **2023**, *23*, 599–604.
72. Micu, M.M.; Chiurciu, I.-A.; Soare, E.; Mituko Vlad, I.; Buzatu, C.; Fulgeanu, D.; Smedescu, C. Romania's position in the worldwide trade with sunflower and rape seeds. *Sci. Pap. Ser. -Manag. Econ. Eng. Agric. Rural. Dev.* **2023**, *23*, 129–136.
73. Smedescu, D.; Fîntîneru, G.; Tudor, V.C.; Smedescu, C.; Fîntîneru, A.; Beia, S. Employment trends in European Union's meat processing companies: A ten-year perspective, 2011–2020. *Sci. Pap. Ser. Manag. Econ. Eng. Agric. Rural. Dev.* **2024**, *24*, 909–922.
74. Mițuko Vlad, I.; Fîntîneru, G.; Burcea, M.; Butcaru, A.C.; Certan, I.; Stanciu, T. LCA and LCCA Methods in Apple Orchard Management, Conventional and Organic. *Bull. Univ. Agric. Sci. Vet. Med. Cluj-Napoca. Hortic.* **2021**, *78*, 8–12. [CrossRef]

75. Nijloveanu, D.; Tița, V.; Bold, N.; Fîntîneru, G.; Smedescu, D.; Chiurciu, I.-A.; Smedescu, C.; Popescu, D.A.; Matei, M.G.; Gheorghe Pătrăchioiu, N. A Mathematical Model of Waste Management and Food Loss along the Agrifood Chain. *Ann. Univ. Oradea Fascicle: Ecotoxicol. Anim. Sci. Food Sci. Technol.* 2023, pp. 50–55. Available online: https://protmed.uoradea.ro/nou/images/Publicatii/Ecotox/2023B/Agroturism/10._Nijloveanu.pdf (accessed on 1 August 2024).
76. Nijloveanu, D.; Tița, V.; Bold, N.; Dinu, T.A.; Peticilă, A.G.; Smedescu, C.A.; Mihalașcu, C.; Stoian, M. Developing an integrated model on food waste consumer behaviour in Romania. *Sci. Pap. Ser. Manag. Econ. Eng. Agric. Rural. Dev.* **2023**, *23*, 617–624.
77. Nijloveanu, D.; Tița, V.; Bold, N.; Fîntîneru, G.; Smedescu, D.; Chiurciu, I.-A.; Smedescu, C.; Gheorghe Pătrăchioiu, N. Dynamics of food loss and waste causes along the agrifood chain in Romania. *Sci. Pap. Ser. Manag. Econ. Eng. Agric. Rural. Dev.* **2023**, *23*, 569–580.
78. Nijloveanu, D.; Tița, V.; Bold, N.; Chiurciu, I.A.; Smedescu, C. Research on the causes of the food waste phenomenon in the European Union. *Bulg. J. Agric. Sci.* **2023**, *29* (Suppl. S1), 132–139.
79. Nijloveanu, D.; Tița, V.; Bold, N.; Dinu, T.A.; Fîntîneru, G.; Smedescu, D.; Peticilă, A.G.; Smedescu, C.; Fîntîneru, A.; Mihalașcu, C. Developing a model based on a statistical analysis of food loss and waste patterns. *Sci. Pap. Ser. Manag. Econ. Eng. Agric. Rural. Dev.* **2024**, *24*, 705–712.
80. Nijloveanu, D.; Tița, V.; Bold, N.; Smedescu, D.; Fîntîneru, A.; Tudor, V.C.; Smedescu, C.; Jerca, E. A statistical study analysis on exploring consumption patterns regarding food loss and waste. *Sci. Pap. Ser. Manag. Econ. Eng. Agric. Rural. Dev.* **2024**, *24*, 685.
81. Lubura, J.; Pezo, L.; Sandu, M.A.; Voronova, V.; Donsì, F.; Šic Žlabur, J.; Ribić, B.; Peter, A.; Šurić, J.; Brandić, I.; et al. Food Recognition and Food Waste Estimation Using Convolutional Neural Network. *Electronics* **2022**, *11*, 3746. [CrossRef]
82. Heshmati, R.A.A.; Mokhtari, M.; Shakiba Rad, S. Prediction of the Compression Ratio for Municipal Solid Waste Using Decision Tree. *Waste Manag. Res.* **2014**, *32*, 64–69. [CrossRef]
83. Shopnil, M.; Husna, A.; Sultana, S.; Islam, M.N. An Ensemble ML Model to Predict the Wastage of Food: Towards Achieving Food Sustainability. In Proceedings of the 2023 IEEE Conference on Networked and Computational Intelligence, Gazipur, Bangladesh, 16–17 June 2023; pp. 1–6. [CrossRef]