Digitalisation of Food Waste Valorisation: Application of Machine Learning Tools in Optimising the Composition of a Functional Food Product

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Review
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Abstract

Food waste represents a significant environmental, economic, and social challenge worldwide. The transition from conventional waste management practices toward circular bioeconomy concepts has encouraged the development of innovative food waste valorisation strategies aimed at recovering high-value compounds, functional ingredients, biofuels, and other value-added products. Recent advances in digital technologies have considerably enhanced the efficiency and sustainability of these processes. This review provides an overview of contemporary food waste valorisation approaches, including biological, chemical, and physical methods, and highlights the role of digital tools in improving process performance and product development. Particular emphasis is placed on the application of machine learning techniques in the optimisation of functional food products formulated from food waste-derived ingredients. Modern digital frameworks integrate data collected through advanced analytical methods, Internet of Things (IoT) systems, and sensor technologies, enabling real-time monitoring and data-driven decision-making. Machine learning models, such as artificial neural networks (ANNs), support vector machines (SVMs), random forests (RFs), and principal component analysis (PCA), facilitate prediction of product quality, optimisation of processing conditions, and identification of optimal ingredient formulations. Furthermore, software platforms including Python, MATLAB, Aspen Plus, and KNIME support modelling, simulation, visualisation, and optimisation of food waste valorisation processes. Despite the considerable potential of digitalisation, challenges related to data quality, technological infrastructure, model interpretability, economic feasibility, and regulatory compliance remain significant barriers to industrial implementation. Future developments are expected to focus on explainable artificial intelligence (XAI), digital twins, blockchain technologies, precision nutrition, and fully integrated smart biorefineries. The integration of digital technologies with food waste valorisation offers substantial opportunities for improving resource efficiency, reducing environmental impacts, and supporting the development of sustainable and innovative food systems.

Keywords

Food waste valorisation, machine learning, functional foods, digitalisation, circular bioeconomy

1 Introduction

Food waste is a pressing global issue with significant environmental, economic, and social implications. Defined as food that is discarded or left uneaten, food waste occurs at various stages of the food supply chain, from production and processing to retail and consumption. According to the Food and Agriculture Organisation (FAO), approximately one-third of all food produced globally is wasted, amounting to about 1.3 billion tons annually.[1] This staggering figure not only represents a waste of resources, such as water, land, and labour, but also contributes to environmental problems, including greenhouse gas emissions from decomposing organic matter in landfills. As consumer awareness of these issues grows, addressing food waste has become increasingly critical. The significance of food waste extends beyond mere statistics.[2] It encompasses economic losses, with estimated costs reaching $940 billion annually worldwide.[3] Additionally, food waste exacerbates food insecurity, as millions of people go hungry while vast quantities of food are discarded. Current trends indicate that food waste is not only a problem in developed countries, where it often occurs at the consumer level, but also in developing nations, where inefficiencies in the supply chain lead to losses before food even reaches consumers. As awareness and concern about food waste continue to rise, innovative solutions are necessary to mitigate this global challenge.[4]

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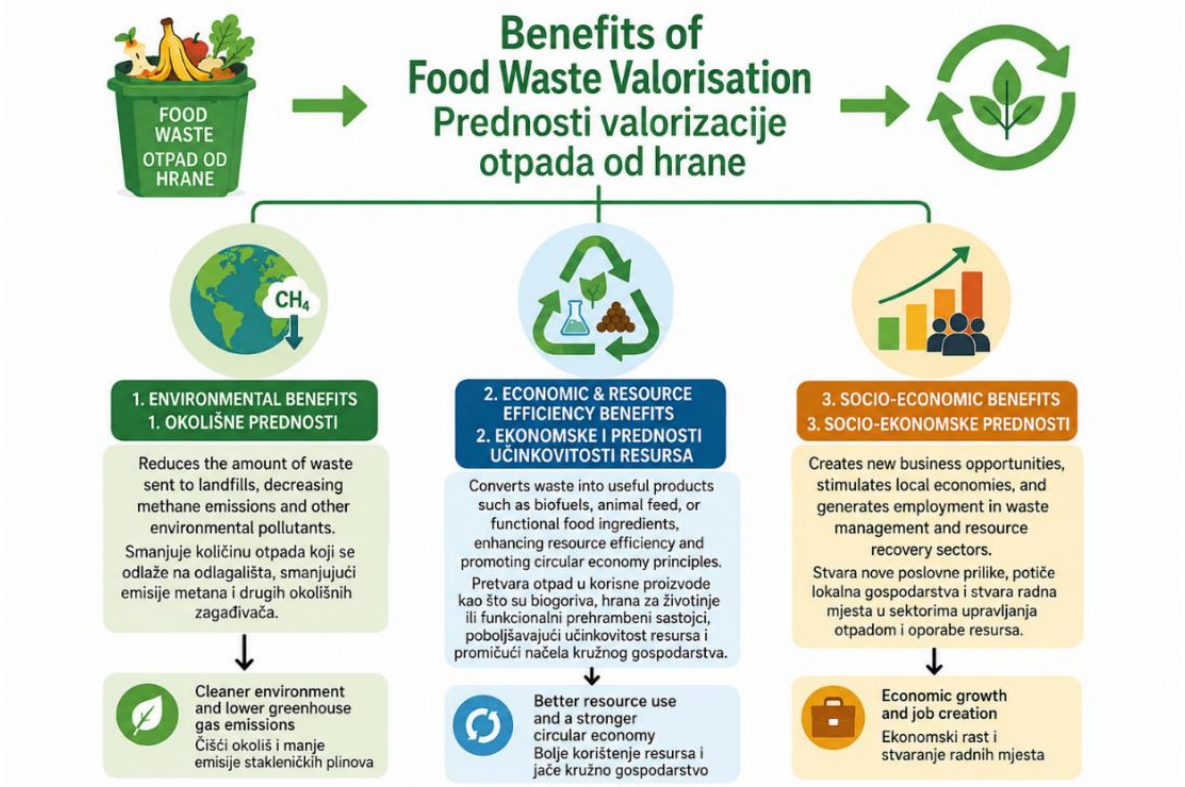


Fig. 1 – Key benefits of food waste valorisation

Slika 1 – Najvažnije prednosti valorizacije otpada od hrane

Food waste valorisation refers to the process of transforming waste into valuable products, thereby reducing the overall waste footprint and contributing to a more sustainable food system.[5,6] The benefits of food waste valorisation are presented in Fig. 1.

Various methods of food waste valorisation are being explored, including biological processes like anaerobic digestion and fermentation, chemical treatments for extracting valuable compounds, and physical processes that convert waste into energy or other products.[7–9] These approaches not only contribute to waste reduction but also enhance the nutritional profile of the resulting products, providing consumers with healthier options.

Digitalisation plays a pivotal role in modern food waste management strategies.[10,11] The integration of digital tools and technologies enables more efficient monitoring, analysis, and optimisation of food waste valorisation processes.[12] Key digital innovations include: (i) advanced data analytics to help identify waste patterns and sources, enabling stakeholders to implement targeted interventions, (ii) internet of things devices to monitor food storage conditions in real-time, reducing spoilage and waste at various points in the supply chain, and (iii) machine learning algorithms to optimise production processes, predict waste generation, and enhance the formulation of valorised products based on consumer preferences.[10–12] By harnessing these digital technologies, the food industry can move towards a more sustainable model that not only reduces waste but also maximises resource utilisation. The purpose of this review is to explore the digitalisation of food waste valorisation, focusing on the application of machine learning tools in optimising the composition of functional food products derived from waste. Unlike broader reviews addressing machine learning applications in food science, this review specifically examines digital technologies within the food waste valorisation chain, linking waste characterisation, recovery of valuable compounds, process monitoring and optimisation, and the development of functional food products. Particular attention is given to the integration of data acquisition, sensing technologies, machine learning models, and computational tools as a framework for improving the efficiency, sustainability, and scalability of food waste valorisation processes.

2 Machine learning in food science

Machine learning (ML) has emerged as a transformative technology in various sectors, including food science. By leveraging data-driven algorithms, machine learning enhances decision-making, optimises processes, and fosters innovation.[13] This section describes the definition and

types of machine learning, followed by its applications in product development, quality control, and predictive analytics within the food industry.

2.1 Overview of machine learning technologies

Machine learning is a subset of artificial intelligence (AI) that enables systems to learn from data, identify patterns, and make decisions with minimal human intervention. Rather than being explicitly programmed to perform a specific task, ML algorithms improve their performance as they are exposed to more data over time.[14] This adaptive learning capability makes machine learning particularly valuable in dynamic environments like food science, where data is abundant and constantly evolving. Machine learning can be broadly categorised into three main types: supervised learning, unsupervised learning, and reinforcement learning. The specific characteristics of different ML types are given in Table 1.

2.2 Applications of machine learning in food science

Machine learning is revolutionising various facets of food science, from product development to quality control and predictive analytics.[18–20] Here, we explore its key applications in greater detail. The list of some of the efficient examples of application of ML in food sciences are given in Table 2. The *product development* process in the food industry involves creating new products or improving existing ones. Machine learning enhances this process by providing insights that guide formulation and innovation. Machine learning algorithms analyse vast datasets of ingredient combinations and their effects on product attributes, such as taste, texture, and nutritional content.[21–23] This analysis enables food developers to identify optimal ingredient ratios and formulations, resulting in innovative products that meet consumer demands.[24] By utilising consumer feedback and sensory data, machine learning can uncover trends in consumer preferences, allowing companies to tailor their offerings to market demands. For example, clustering algorithms can segment consumers based on taste preferences, dietary restrictions, or purchasing behaviours, aiding in targeted product development.[25] Furthermore, machine learning accelerates the prototyping phase by predicting the outcomes of new formulations before they are physically created.[26] This predictive capability reduces time and costs associated with trial-and-error approaches in product development. These capabilities are particularly relevant to the development of functional food products derived from food-industry by-products. ML models can link the composition and properties of recovered ingredients with formulation variables and final product characteristics, enabling the simultaneous consideration of nutritional value, bioactive compound content, sensory properties, texture, and stability. In this way, digitalisation can support not only the recovery of valuable components from food waste but also their subsequent incorporation into optimised value-added food products. Ensuring *consistent quality* is important in the food industry, and machine learning plays a crucial role in enhancing quality control processes.

Machine learning algorithms can analyse images of food products to detect defects or inconsistencies, such as discolouration, size variations, or packaging.[27,28] This real-time analysis enables manufacturers to identify quality issues early in the production process, reducing waste and ensuring that only high-quality products reach consumers. With the increasing use of IoT devices in food production, machine learning can analyse data from sensors that monitor critical variables such as temperature, humidity, and pH levels.[29,30] By correlating these variables with product quality, ML models can provide actionable insights for maintaining optimal conditions throughout the production and storage processes. Machine learning can also be applied to predict equipment malfunctions or maintenance needs based on historical performance data.[31] By analysing sensor data from machinery, manufacturers can schedule maintenance proactively, reducing downtime and ensuring consistent production quality. In food waste valorisation, similar sensor- and data-driven approaches can support the characterisation of heterogeneous waste and by-product streams and the monitoring of valorisation processes. Spectroscopic and sensor data can be combined with ML models to predict relevant physicochemical properties or the content of target bioactive compounds, while real-time monitoring of variables such as temperature, pH, and other process parameters can provide information required for process control. Such approaches are particularly relevant for extraction, fermentation, and other bioprocesses in which variability in the composition of the starting material can substantially influence process performance and the quality of recovered products.[8] *Predictive analytics* involves using historical data to forecast future outcomes, enabling businesses to make informed decisions. In food science, machine learning enhances predictive analytics in several ways. Machine learning models can predict the shelf life of food products[30,32] by analysing factors such as composition, storage conditions, and microbiological data. This information helps manufacturers optimise inventory management and reduce food waste by accurately forecasting when products will reach the end of their usable life.[33] Machine learning can also be applied to predict potential health and safety risks associated with food products.[34–36] By analysing data on foodborne pathogens, contamination sources, and environmental conditions, ML models can identify risks and inform preventive measures, enhancing food safety. Within food waste valorisation, predictive modelling can additionally be used to relate raw-material characteristics and processing conditions to valorisation outcomes. For example, ML models can support the

Table 1 – Machine learning types[12–17]

Tablica 1 – Vrste strojnoga učenja[12–17]

Machine learning type Vrsta strojnog učenja	Definition Definicija	Data type used Korišteni tip podataka	Main objective Glavni cilj	Common techniques / algorithms Uobičajena tehnike/algoritmi	Applications in food science and food waste valorisation Primjene u znanosti o hrani i valorizaciji otpada od hrane	Key advantages Ključne prednosti	Limitations Ograničenja
Supervised learning	A machine learning approach where algorithms are trained using labelled datasets containing input-output relationships.	Labelled data.	Predict outcomes or classify data based on known examples.	Regression analysis, decision trees, RF, SVMs, ANN.	Prediction of food quality, shelf-life estimation, optimisation of extraction conditions, classification of food waste streams, prediction of bioactive compound yield.	High prediction accuracy, suitable for optimisation and forecasting.	Requires large labelled datasets and extensive training data.
Nadzirano učenja	Pristup strojnom učenju gdje se algoritmi obučavaju primjenom označenih skupova podataka koji sadrže odnose ulaz-izlaz.	Označeni podatci.	Predviđanje ishoda ili klasificiranje podataka na temelju poznatih primjera.	Regresijska analiza, stabla odlučivanja, slučajna šuma, strojevi potpornih vektora (SVM), umjetne neuronske mreže (ANN)	Predviđanje kvalitete hrane, procjena roka trajanja, optimiranje uvjeta ekstrakcije, klasifikacija tokova otpada od hrane, predviđanje prinosa bioaktivnih spojeva.	Visoka točnost predviđanja, pogodno za optimiranje i predviđanje.	Zahtijeva velike označene skupove podataka i opsežne podatke za obuku
Unsupervised learning	A learning method where algorithms identify hidden patterns or structures in unlabelled datasets.	Unlabelled data.	Discover relationships, clusters, or trends within the data.	Clustering, k-means, hierarchical clustering (PCA), dimensionality reduction.	Consumer preference segmentation, grouping food waste by composition, analysis of sensory data, identification of processing patterns.	Useful when labelled data are unavailable, identifies hidden relationships.	Results may be difficult to interpret and validate.
Nenadzirano učenje	Metoda učenja u kojoj algoritmi identificiraju skrivene obrasce ili strukture u neoznačenim skupovima podataka.	Neoznačeni podatci.	Otkrivanje odnosa, klastera ili trendova unutar podataka.	Grupiranje, k-srednje vrijednosti, hijerarhijsko grupiranje, analiza glavnih komponenti (PCA), smanjenje dimenzionalnosti	Segmentacija preferencija potrošača, grupiranje otpada od hrane prema sastavu, analiza senzornih podataka, identifikacija obrazaca obrade.	Korisno kada označeni podatci nisu dostupni, identificira skrivene odnose.	Rezultate može biti teško interpretirati i validirati.

Table 1 – (continued)
Tablica 1 – (nastavak)

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Reinforcement learning	A machine learning method where an agent learns through interaction with the environment using rewards and penalties.	Dynamic interaction data.	Optimise sequential decision-making processes.	Q-learning, deep reinforcement learning, policy gradient methods.	Optimisation of food production processes, smart inventory management, process automation, optimisation of resource allocation in biorefineries.	Adaptive learning, effective for complex optimisation problems.	Computationally intensive and requires continuous feedback.
Učenje s potkrepljenjem odluka	Metoda strojnog učenja u kojoj agent uči kroz interakciju s okolinom koristeći nagrade i kazne.	Dinamički podatci o interakciji.	Optimiranje procesa sekvencijalnog donošenja odluka.	Q-učenje, duboko učenje s potkrepljenjem, metode gradijenta politike.	Optimiranje procesa proizvodnje hrane, pametno upravljanje zalihama, automatizacija procesa, optimizacija alokacije resursa u biorafinerijama.	Adaptivno učenje, učinkovito za složene probleme optimizacije.	Računalno intenzivno i zahtijeva kontinuiranu povratnu informaciju.
Deep learning	Advanced subset of machine learning using multi-layer neural networks to process large and complex datasets.	Large structured or unstructured datasets.	Learn highly complex patterns and representations.	Convolutional neural networks (CNN), recurrent neural networks (RNN), deep neural networks (DNN).	Image-based food quality inspection, defect detection, predictive modelling in food processing, automated waste sorting.	Handles large and complex datasets with high accuracy.	Requires high computational power and large datasets.
Duboko učenje	Napredni podskup strojnog učenja primjenom višeslojnih neuronskih mreža za obradu velikih i složenih skupova podataka.	Veliki strukturirani ili nestrukturirani skupovi podataka.	Učenje vrlo složenih obrazaca i reprezentacija.	Konvolucijske neuronske mreže (CNN), Rekurentne neuronske mreže (RNN), Duboke neuronske mreže (DNN).	Inspekcija kvalitete hrane temeljena na slikama, otkrivanje nedostataka, prediktivno modeliranje u preradi hrane, automatizirano sortiranje otpada.	Obrađuje velike i složene skupove podataka s visokom točnošću.	Zahtijeva veliku računalnu snagu i velike skupove podataka.

Table 1 – (continued)
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Semi-supervised learning	Combines small amounts of labelled data with large amounts of unlabelled data during training.	Both labelled and unlabelled data.	Improve learning accuracy when labelled data are limited.	Semi-supervised SVM, self-training models.	Food classification, quality prediction with limited experimental data.	Reduces labelling effort and improves model efficiency.	Model performance depends on data quality.
Polunadzirano učenje	Kombinira male količine označenih podataka s velikim količinama neoznačenih podataka tijekom učenja.	I označeni i neoznačeni podatci.	Poboljšava točnost učenja kad su označeni podatci ograničeni.	Polunadzirani SVM, modeli za samoučenje.	Klasifikacija hrane, predviđanje kvalitete s ograničenim eksperimentalnim podatcima.	Smanjuje napor označavanja i poboljšava učinkovitost modela.	Performanse modela ovise o kvaliteti podataka.
Transfer learning	A method where knowledge gained from one task is applied to another related task.	Pre-trained datasets.	Reduce training time and improve model performance.	Pre-trained neural networks, fine-tuning models.	Food image recognition, rapid adaptation of food quality models.	Faster training and reduced data requirements.	Limited by similarity between tasks.
Transfer učenja	Metoda u kojoj se znanje stečeno iz jednog zadatka primjenjuje na drugi povezani zadatak.	Prethodno obučeni skupovi podataka.	Smanjenje vremena obuke i poboljšanje performansi modela.	Prethodno obučene neuronske mreže, modeli finog podešavanja.	Prepoznavanje slike hrane, brza prilagodba modela kvalitete hrane.	Brže obučavanje i smanjeni zahtjevi za podatcima.	Ograničeno sličnošću između zadataka.
Explainable artificial intelligence (XAI)	AI approaches designed to make machine learning decisions interpretable and transparent.	Structured and unstructured data.	Improve understanding and trust in AI systems.	SHAP, LIME, explainable neural networks. SHAP, LIME,	Transparent decision-making in food safety, process optimisation, regulatory compliance.	Enhances trust and interpretability.	May reduce model complexity and prediction performance.
Objašnjiva umjetna inteligencija (XAI)	Pristupi umjetnoj inteligenciji osmišljeni kako bi odluke strojnog učenja bile interpretabilne i transparentne.	Strukturirani i nestrukturirani podatci.	Poboljšavaju razumijevanje i povjerenje u AI sustave.	Objašnjive neuronske mreže.	Transparentno donošenje odluka u sigurnosti hrane, optimiranju procesa, usklađenosti s propisima.	Povećava povjerenje i interpretabilnost.	Može smanjiti složenost modela i učinkovitost predviđanja.

Table 2 – Application of ML methods in food science
Tablica 2 – Primjena metoda strojnog učenja u znanosti o hrani

Modelling approach Pristup modeliranju	Usage Primjena	Results Rezultati	Ref. Lit.
Decision tree, RF, SVM, logistic regression (LR), k-nearest neighbours (KNN), and extreme gradient boosting (XGBoost).	Applicability of machine learning techniques in the categorisation of food ingredients into healthy and unhealthy.	XGBoost outperformed all other models, with an average accuracy of 94 %, demonstrating its better generalisation and predictive power based on the ensemble gradient boosting technique.	21
Stablo odlučivanja, slučajna šuma, stroj potpornih vektora, logistička regresija, K-najbliži susjedi i ekstremno pojačavanje gradijenta ansambla.	Primjenjivost tehnika strojnog učenja u kategorizaciji sastojaka hrane u zdrave i nezdrave.	XGBoost je nadmašio sve ostale modele, s prosječnom točnošću od 94 %, pokazujući svoju bolju generalizaciju i prediktivnu moć na temelju tehnike pojačavanja gradijenta.	
Ridge, RF XGBoost, KNN, multilayer perceptron (MLP).	Prediction of hardness and chewiness of the meat analogues based on proximate compositions of the raw materials (protein, fat, carbohydrate, fibre, ash, and moisture).	Mean absolute percentage error (MAPE) of 22.9 %, root mean square error (RMSE) of 10.101 for hardness, MAPE of 14.5 %, and RMSE of 6.035 for chewiness using Ridge approach.	22
Ridge, Slučajna šuma, KNN, višeslojne preceptronske mreže (MLP)).	Predviđanje tvrdoće i žvakavosti mesnih analoga na temelju približnog sastava sirovina (proteini, masti, ugljikohidrati, vlakna, pepeo i vlaga).	Srednja apsolutna postotna pogreška (MAPE) od 22,9 %, korijen srednje kvadratne pogreške (RMSE) od 10,101 za tvrdoću, MAPE od 14,5 % i RMSE od 6,035 za žvakavost primjenom Ridge pristupa.	
PSO-SVM, a convolutional neural network (CNN), and a long short-term memory network (LSTM) model.	Prediction of blueberries sensory evaluation scores based on ten physical and chemical flavour indices (such as catalase, flavonoids, and soluble solids).	Root mean square error and mean absolute error of the particle swarm optimisation support vector machine were 0.45 and 0.40.	37
Stroj potpornih vektora optimizacije roja čestica, konvolucijska neuronska mreža i model mreže dugog kratkoročnog pamćenja.	Predviđanje senzornih rezultata borovnica na temelju deset fizikalnih i kemijskih indeksa okusa (kao što su katalaza, flavonoidi i topljive tvari).	Korijen srednje kvadratne pogreškei srednja apsolutna pogreška stroja potpornih vektora optimizacije roja čestica bile su 0,45 i 0,40.	
LightGBM.	Prediction of flavour quality of green coffee beans based on visible/near-infrared hyperspectral imaging data.	Highest discrimination accuracies of 99 % and 97 %, in the internal validation and external evaluation.	23
LightGBM.	Predviđanje kvalitete okusa zelenih zrna kave na temelju podataka. hiperspektralnog snimanja u vidljivom/bliskom infracrvenom području	Najviša točnost razlikovanja od 99 % i 97 %, u internoj validaciji i vanjskoj evaluaciji.	
Deep learning (Dl4jMlpClassifier) and traditional ML models (RF, LogitBoost, subspace discriminant (Ensemble), WiSARD, medium Gaussian SVM, and wide neural network.	Classifying biscuits enriched with various types and concentrations of *Chlorella microalgae* based on texture features extracted from digital images.	The highest classification correctness, reaching 97.86 %, was obtained with the subspace discriminant algorithm.	24
Duboko učenje (Dl4jMlpClassifier) i tradicionalni modeli strojnog učenja (Random Forest, LogitBoost, Subspace Discriminant (Ensemble), WiSARD, Medium Gaussian SVM i Wide Neural Network).	Klasifikacija keksa obogaćenih različitim vrstama i koncentracijama mikroalgi Chlorella na temelju teksturnih značajki izdvojenih iz digitalnih slika.	Najviša točnost klasifikacije, koja je dosegla 97,86 %, postignuta je algoritmom Subspace Discriminant	
SVM.	Differentiation between fresh and rotten apples based on the data gathered using two gas sensors.	99.6 % accuracy in differentiation between fresh and rotten apples.	29
Stroj potpornih vektora (SVM)	Razlikovanje svježih i trulih jabuka na temelju podataka prikupljenih pomoću dva plinska senzora.	Točnost od 99,6 % u razlikovanju svježih i trulih jabuka.	
LR and partial least squares-discriminant analysis (PLS-DA) as baseline linear models, RF and XGB).	Predicting consumer preferences of melon flavour and sensory attributes.	The random forest model effectively predicted (accuracy of 0.94) volatile compounds responsible for melons flavour.	25
Logistička regresija (LR) i analiza parcijalnih najmanjih kvadrata s diskriminantnom analizom (PLS-DA) kao osnovni linearni modeli, slučajna šuma (RF) i XGBoost (XGB)	Predviđanje preferencija potrošača u pogledu okusa dinje i senzornih svojstava.	Model slučajne šume učinkovito je (točnost od 0,94) predvidio hlapljive spojeve odgovorne za okus dinje.	

Table 2 – (continued)
Tablica 2 – (nastavak)

Modelling approach Pristup modeliranju	Usage Primjena	Results Rezultati	Ref. Lit.
KNN, SVM, ANN, LR, RF. K-NN, SVM, ANN, logistička regresija, slučajna	Classification of the freshness of fish from the freshness of the fish eyes (FFE) dataset. Klasifikacija svježine ribe iz skupa podataka o svježini ribljih očiju (FFE).	ANN ensured 73 % accuracy. ANN je osigurala točnost od 73 %.	27
Fully connected neural network (FCNN). Potpuno povezane neuronske mreže (FCNN).	Classification of the date fruit freshness using IoT-based on real time multichannel gas sensors data. Klasifikacija svježine datulja pomoću potpuno povezane neuronske mreže (FCNN) temeljene na podatcima. višekanalnih plinskih senzora u stvarnom vremenu temeljenim na IoT-u.	Classification accuracy of 91.9 %. Točnost klasifikacije od 91,9 %.	30
XGBoost, RF, and support vector regression (SVR). XGBoost, RF i support vector regression (SVR).	Prediction of sprouting and shrinkage of potatoes based on data including storage duration, temperature, moisture, vitamin C, and sugar content, over a six-month period. Predviđanje klijanja i skupljanja krumpira na temelju podataka koji uključuju trajanje skladištenja, temperaturu, vlagu, vitamin C i sadržaj šećera, tijekom razdoblja od šest mjeseci.	XGBoost showed the highest prediction accuracy with R^2 values of 0.997 and 0.986 for shrinkage and sprouting predictions. XGBoost je pokazao najveću točnost predviđanja s vrijednostima R^2 od 0,997 i 0,986 za predviđanja skupljanja i klijanja.	33
PCA, discriminant factor analysis (DFA) and SVM. Analiza glavnih komponenti (PCA), analiza diskriminantnih faktora (DFA) i metodom potpornih vektora (SVM).	Classification of fungal contamination in brown rice grain based on the hyperspectral imaging. Klasifikacija gljivične kontaminacije u zrnu smeđe riže na temelju hiperspektralnog snimanja.	Among the evaluated methods, hyperspectral imaging integrated with a Gaussian SVM provided the highest classification accuracy (93.4 %) for rice samples with varying contamination percentages. Među evaluiranim metodama, hiperspektralno snimanje integrirano s Gaussovim SVM-om pružilo je najveću točnost klasifikacije (93,4 %) za uzorke riže s različitim postotcima kontaminacije.	34
One-dimensional convolution neural networks (1D-CNN), transformer. Jednodimenzionalne konvolucijske neuronske mreže (1D-CNN), transformer	Prediction of soybean fungal contamination based on visible and near-infrared and short-wave infrared hyperspectral imaging data. Predviđanje kontaminacije soje mikroskopskim gljivama na temelju podataka hiperspektralnog snimanja u vidljivom i bliskom infracrvenom i kratkovalnom infracrvenom području.	The low-level fusion (LLF) strategy coupled with a 1D-CNN achieved the highest accuracy of 97.52 %, while the intermediate-level (ILF) strategy using a transformer model reached 95.71 % accuracy. Strategija niske razine fuzije (LLF) povezana s 1D-CNN postigla je najveću točnost od 97,52 %, dok je strategija srednje razine (ILF) korištenjem transformatorskog modela dosegla točnost od 95,71 %.	35
Hybrid convolutional transformer-feature fusion network. Hibridna mreža za fuziju konvolucijskih transformatora i značajki.	Detection of *Aspergillus flavus* contamination in peanut kernels using visible–near-infrared (VNIR) hyperspectral imaging and hyperspectral microscopic imaging (HMI). Detekcija kontaminacije *Aspergillus flavus* u zrnima kikirikija primjenom hiperspektralnog snimanja u vidljivom-bliskom infracrvenom (VNIR) području i hiperspektralnog mikroskopskog snimanja (HMI).	Accuracy of 100.00 % for both VNIR hyperspectral imaging and HMI. Točnost od 100,00 % za VNIR hiperspektralno snimanje i HMI.	36
SVM, 1D-CNN, residual networks (ResNet, ResNeXt, RegNet). SVM, 1D-CNN, rezidualne mreže (ResNet, ResNeXt, RegNet).	Detection of Cu concentration in rapeseed based on hyperspectral imaging data. Detekcija koncentracije Cu u uljnoj repici na temelju hiperspektralnih snimaka.	The best performance was obtained using hyperspectral false-colour images combined with the RegNetX-6.4GF deep learning model, which achieved 98.15 % accuracy (Macro-F1 = 98.15 %) in detecting and classifying Cu stress in rapeseed. Najbolje performanse postignute su primjenom hiperspektralnih slika u lažnim bojama u kombinaciji s modelom dubokog učenja RegNetX-6.4GF, koji je postigao točnost od 98,15 % (Macro-F1 = 98,15 %) u detekciji i klasifikaciji stresa Cu u uljnoj repici.	38

prediction of extraction yield, recovery of bioactive compounds, or properties of the resulting extracts as a function of process variables such as temperature, extraction time, solvent composition, and solid-to-liquid ratio. When combined with optimisation approaches, such models can facilitate the identification of processing conditions that maximise recovery and product quality while reducing experimental effort and resource consumption. Although these studies demonstrate the broad potential of ML in food science, their direct transfer to food waste valorisation is not always straightforward. Food waste represents a particularly challenging matrix because its composition varies considerably with raw material origin, season, processing history, and storage conditions. Consequently, ML models developed for well-defined food matrices may not exhibit comparable robustness when applied to heterogeneous waste streams. Nevertheless, the methodological advances summarised in Table 2 provide an important basis for developing predictive models specifically tailored to food waste characterisation, extraction optimisation, process monitoring, and the formulation of value-added products from recovered compounds. Therefore, the relevance of ML to food waste valorisation extends across the entire valorisation chain, from waste-stream characterisation, and the optimisation and monitoring of recovery processes to the formulation and quality assessment of the final functional product. However, studies integrating these stages within a single digital framework remain limited, highlighting an important opportunity for future research.

3 Food waste valorisation approaches

Food waste valorisation represents a paradigm shift from traditional waste management to a circular bioeconomy model.[39] Rather than disposing of organic waste in landfills, where it generates potent greenhouse gases, valorisation strategies seek to transform these materials into high-value bioproducts, biofuels, and functional ingredients.[5,40,41] These approaches are broadly categorised into biological, chemical, and physical valorisation methods (Fig. 2).

Biological valorisation utilises living organisms or their cellular components to break down and transform complex food waste streams into commercial products under mild operating conditions. *Solid-state and submerged fermentation* utilise microorganisms like bacteria, yeast, and fungi to metabolise food waste.[42] In anaerobic digestion, microbial consortia convert organic matter into biogas (methane and carbon dioxide), providing a renewable energy source.[43] Alternatively, precision fermentation can steer this metabolic breakdown toward high-value platform chemicals, such as lactic acid, ethanol, and polyhydroxyalkanoates (PHAs), which serve as precursors for biodegradable bioplastics. *Enzymatic treatment* employs specific biocatalysts, such as proteases, cellulases, and lipases, to selectively hydrolyse complex macromolecules. Unlike microbial fermentation, enzymatic treatment offers precise control over the final product profile without the risk of microbial contamination.[44] It is highly effective for recovering bioactive peptides from protein-rich waste or converting lignocellulosic food residues into fermentable sugars, operating efficiently at lower temperatures and atmospheric pressure.

Chemical valorisation relies on chemical reactions and solvent interactions to extract valuable compounds or structurally alter food waste molecules into new functional materials. Food waste, particularly fruit peels, vegetable trimmings, and spent grains, is rich in bioactive compounds such as polyphenols, essential oils, and carotenoids.[45–47] Traditional solvent extraction is increasingly being replaced by green extraction technologies. Supercritical fluid extraction (typically using carbon dioxide) and ultrasound- or microwave-assisted extractions isolate these high-value antioxidants and antimicrobials with minimal environmental impact, preparing them for use in the pharmaceutical, cosmetics, and food industries. Furthermore, chemical transformations involve altering the chemical structure of waste components through targeted reactions like esterification, transesterification, or acid/base hydrolysis. A primary application is the transesterification of waste cooking oils and animal fats with alcohols to produce biodiesel.[48] Additionally, chemical modification of food-derived polysaccharides (like chitin from seafood waste or starch from potato peels) can yield functional hydrogels, emulsifiers, and biobased adhesives.[48]

Physical valorisation techniques alter the physical state, particle size, or thermal energy of food waste, acting either as a standalone valorisation pathway or as a crucial pretreatment phase to enhance subsequent biological or chemical processes. Mechanical processing includes sorting, crushing, milling, and homogenisation.[49] By reducing particle size, mechanical processing dramatically increases the specific surface area of the waste. This maximises the accessibility of the substrate for enzymes or chemical solvents in downstream processing. Dewatering and drying are also vital mechanical steps that reduce moisture content, stabilising the waste against microbial decay and lowering transportation costs.[50]

4 Digital tools for food waste valorisation

The integration of digital technologies into food waste valorisation has significantly transformed traditional approaches to the recovery of high-value bioactive compounds agro-industrial residues.[51] In contrast to conventional empirical methods, modern digital frameworks enable data-driven decision-making, process optimisation, and predictive modelling, thereby improving efficiency, sustainability, and scalability. The application of Internet of Things (IoT) systems, machine learning (ML) algorithms, and advanced software platforms

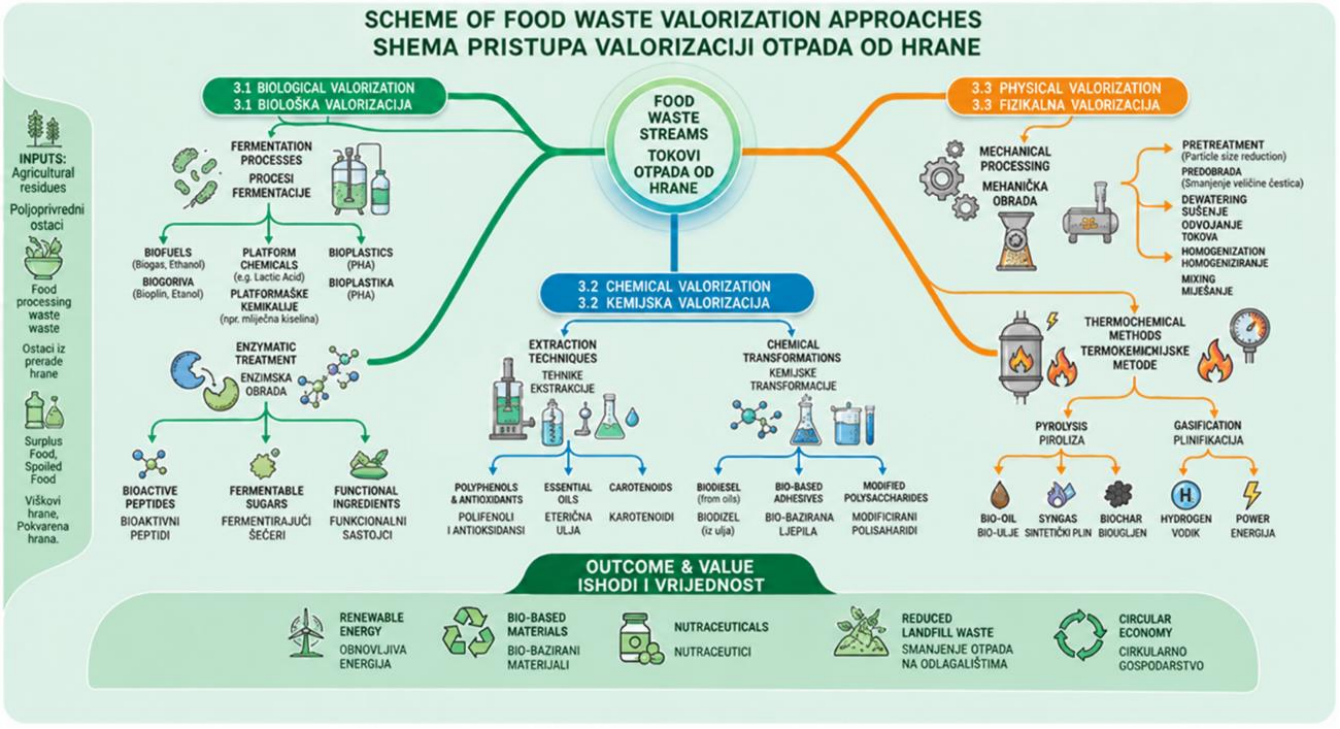


Fig. 2 – Food waste valorisation approaches
Slika 2 – Pristupi valorizaciji otpada od hrane

has facilitated the development of smart biorefineries in which food waste is systematically converted into valuable chemicals, materials, and energy carriers.[52]

4.1 Data collection and analysis

The development of functional food products from food waste requires extensive and multidimensional data collection. Unlike conventional food processing systems, functional food design incorporates not only physicochemical properties but also nutritional, bioactive, and sensory attributes.[53] Key datasets include compositional information of food waste-derived ingredients such as dietary fibre, proteins, lipids, phenolic compounds, and micronutrients. In addition, data on antioxidant capacity, glycaemic response potential, and bioaccessibility of active compounds are essential for evaluating functional performance. Process-related data also play a crucial role in optimising product formulation. These include extraction conditions for bioactive recovery (temperature, solvent type, time, and enzyme concentration), formulation ratios of ingredients, processing conditions such as drying, fermentation, or extrusion, and storage stability parameters. Sensory data, including taste, texture, aroma, and overall acceptability, are also increasingly integrated into digital models to ensure consumer-oriented product development. Modern digitalisation relies heavily on Internet of Things (IoT) systems and advanced sensing technologies for real-time data acquisition.[54,55] Spectroscopic techniques such as near-infrared (NIR), hyperspectral imaging, and Fourier-transform infrared (FTIR) spectroscopy enable rapid characterisation of food waste-derived ingredients without destructive sampling. These techniques allow continuous monitoring of compositional changes during processing and storage. In parallel, IoT-enabled sensors embedded in processing equipment provide real-time measurements of temperature, pressure, moisture, and flow rates, ensuring precise control of functional food production systems.[55] The integration of these data sources into centralised cloud-based platforms enables large-scale data storage and analysis. This facilitates the development of predictive models that support decision-making in both extraction and formulation stages, thereby improving efficiency and product consistency.

4.2 Machine learning models in valorisation

Machine learning plays a central role in optimising the composition and performance of functional food products derived from food waste.[56] These models enable the prediction of optimal ingredient combinations, processing conditions, and functional properties based on historical and experimental data. In functional food design, machine learning ap-

proaches are used to balance multiple objectives simultaneously, such as maximising nutritional value, enhancing bioactivity, and improving sensory acceptability. Supervised learning techniques are widely applied in this domain. In these models, input variables such as ingredient proportions, processing parameters, and physicochemical properties are mapped to output variables such as antioxidant capacity, texture profile, or sensory scores. Artificial neural networks are particularly effective in modelling nonlinear relationships in complex food systems. They have been used to optimise formulations of functional bakery products enriched with fibre and phenolic-rich extracts from food waste.[57] SVMs are also commonly employed for classification tasks, such as distinguishing between high- and low-quality formulations based on predicted functional properties.[58] RF models provide robust predictive performance and are useful for identifying the most influential variables affecting product quality and stability.[59] Unsupervised learning techniques also play an important role in functional food development. PCA is frequently used to reduce the dimensionality of complex datasets and identify correlations between formulation variables and product characteristics.[60] Cluster analysis methods, such as k-means clustering, are used to group similar food formulations based on nutritional composition or sensory attributes.[61] These techniques help in identifying optimal formulation clusters that meet specific functional and sensory criteria. In addition to traditional machine learning approaches, optimisation algorithms such as genetic algorithms (GAs) and particle swarm optimisation (PSO) are increasingly integrated with ML models to perform multi-objective optimisation.[62] These hybrid systems allow simultaneous optimisation of multiple parameters, including nutritional content, antioxidant activity, texture, and consumer acceptability. Such approaches are particularly valuable in functional food development, where trade-offs between health benefits and sensory quality are common. Despite these advantages, the selection of an appropriate ML approach should depend on the characteristics and size of the available dataset and on the specific valorisation objective. Complex nonlinear models may provide high predictive performance but can require large datasets and may have limited interpretability, whereas simpler models may be more suitable when experimental data are scarce. This issue is particularly relevant in food waste valorisation, where datasets are often relatively small, heterogeneous, and generated under different experimental conditions. Therefore, model performance should not be evaluated solely on prediction accuracy; robustness, external validation, interpretability, and transferability to different waste matrices and processing scales should also be considered. The integration of ML with process knowledge and appropriate experimental design is consequently essential to avoid overfitting and to ensure that data-driven models provide practically meaningful information for valorisation process development.

The suitability of individual ML approaches for food waste valorisation depends strongly on the nature of the available data, the objective of the analysis, and the stage of the valorisation process. ANNs are particularly suitable for modelling complex nonlinear relationships between processing conditions and multiple responses, such as extraction yield, recovery of bioactive compounds, or functional properties of the resulting products. Their main advantage is their ability to approximate highly nonlinear systems without requiring an explicit mathematical description; however, they generally require sufficiently large and representative datasets, and their limited interpretability may restrict mechanistic understanding. SVMs can perform effectively with relatively small and high-dimensional datasets and are therefore particularly useful for classification or prediction based on spectroscopic and sensor data. Nevertheless, their performance depends strongly on kernel selection and parameter optimisation, and they may become computationally demanding for large datasets. RFs provide robust prediction, they can handle nonlinear relationships and interactions, and offer information on variable importance, which makes them useful for identifying influential waste characteristics or processing parameters. However, RF models may be less suitable for extrapolation beyond the experimental domain and may provide less accurate predictions for highly continuous responses than carefully optimised nonlinear models.

Unsupervised methods such as PCA are particularly valuable during the initial characterisation of heterogeneous food waste streams and for reducing the dimensionality of spectroscopic or multivariate datasets, but they are primarily exploratory and do not directly provide predictive process models. In contrast, optimisation algorithms such as GAs and PSO are most advantageous when coupled with predictive models, particularly ANNs, for identifying combinations of operating conditions that maximise recovery yield or product functionality while minimising energy, solvent, or resource consumption. Consequently, no single ML method can be considered universally optimal for food waste valorisation. For heterogeneous, high-dimensional sensor and spectral data, SVM and RF approaches may provide advantages, whereas ANNs are particularly suitable for complex nonlinear process modelling and multi-response prediction. PCA is most useful for exploratory analysis and dimensionality reduction, while hybrid ANN–GA or ANN–PSO approaches are particularly promising for multi-variable process optimisation. Model selection should therefore consider not only predictive accuracy but also dataset size and dimensionality, interpretability, computational requirements, robustness, external validation, and the intended application of the model.

4.3 Software and platforms

The implementation of machine learning-based functional food optimisation is supported by a wide range of software tools and computational platforms. MATLAB and Simulink are widely used for modelling food processing systems and implementing optimisation algorithms. These platforms allow simulation of extraction, formulation, and processing steps involved in functional food production. Python has become one of the most widely used programming languages in this field due to its flexibility and the availability of an extensive ecosystem of libraries for machine learning, data analysis, and data manipulation, including Scikit-learn, TensorFlow, Keras, and Pandas.[63] These tools enable the development of predictive models for formulation optimisation, sensory prediction, and bioactivity estimation. R programming is also widely used for statistical analysis, response surface methodology (RSM), and multivariate data analysis in food formulation studies.[64] For industrial applications, process simulation software such as Aspen Plus and SuperPro Designer is used to model integrated biorefinery systems that include extraction of bioactive compounds, ingredient production, and functional food formulation.[65] These tools allow evaluation of mass balance, energy consumption, and economic feasibility of food waste valorisation processes. Data visualisation platforms such as Tableau and Power BI are increasingly used to interpret complex datasets and support decision-making in functional food development.[66] These tools enable visualisation of relationships between formulation variables and product outcomes, facilitating better communication between researchers, product developers, and industry stakeholders. Workflow automation platforms such as KNIME and RapidMiner further support the integration of data preprocessing, machine learning model development, and optimisation workflows in a single environment.[64]

5 Challenges, limitations, and future perspectives of digitalisation in food waste valorisation

Despite the significant progress achieved in the digitalisation of food waste valorisation and the application of machine learning tools in functional food optimisation, several scientific, technological, economic, and regulatory challenges continue to limit large-scale implementation. The integration of digital technologies into food processing systems requires not only advanced computational tools but also reliable datasets, technological infrastructure, interdisciplinary expertise, and compliance with strict food safety regulations. Furthermore, the complexity and heterogeneity of food waste streams create additional obstacles for the development of standardised predictive models and automated valorisation systems. From an economic perspective, scaling digital solutions from laboratory applications to industrial smart biorefineries requires consideration of both capital expenditures (CAPEX) and operating expenditures (OPEX). CAPEX includes investments in advanced sensors and analytical instruments, automated process-control systems, IoT infrastructure, data acquisition systems, and computing hardware, whereas OPEX includes recurring costs associated with equipment maintenance and calibration, software and data management, cloud computing, cybersecurity, and specialised personnel. These costs may represent a considerable barrier to industrial implementation, particularly for small- and medium-sized enterprises. However, they should be considered in relation to the potential economic benefits of digitalisation, including improved process efficiency and product yield, reduced consumption of energy and raw materials, lower waste generation, and decreased process downtime. Therefore, pilot-scale techno-economic assessment, together with modular and stepwise implementation of digital technologies, is important for determining whether operational savings and increased product value can compensate for the initial investment and support economically feasible scale-up. Addressing these limitations is essential for advancing sustainable food waste management and enabling the industrial-scale production of value-added functional food products. The most important challenges of integrating digital technologies into food waste valorisation and possible future perspectives are given in Table 3. Overall, the studies discussed in this review demonstrate that the scientific significance of digitalisation in food waste valorisation extends beyond the application of individual computational tools. A key contribution of this review is the integration of food waste valorisation technologies with digital data acquisition, advanced analytical and sensing techniques, and ML-assisted process and product optimisation within a common framework. This integrated perspective links different stages of the valorisation chain, from the characterisation of heterogeneous food waste and recovery of valuable compounds to process monitoring, prediction of product properties, and optimisation of functional food formulations. In this context, the combination of ML models with IoT systems, spectroscopic and other sensing technologies, and process simulation represents an important opportunity to transform experimental and process data into predictive information for more efficient and sustainable food waste valorisation.

Future research should increasingly move from isolated applications of digital tools toward integrated, validated, and scalable digital valorisation systems. Particular attention should be directed toward the development of standardised and interoperable datasets, validation of ML models using independent datasets and different food waste matrices, and integration of real-time sensor data with predictive models for adaptive process monitoring and control. XAI and hybrid approaches combining mechanistic and data-driven models are expected to improve model transparency, robustness, and transferability. Digital twins also represent a promising framework for integrating real-time

Table 3 – Key challenges in integrating digital technologies into food waste valorisation and future perspectives[10,11,15,16,20]
Tablica 3 – Najvažniji izazovi integracije digitalnih tehnologija u valorizaciju otpada od hrane i moguće buduće perspektive[11,15,16,20]

Category Kategorija	Key issue Ključni problem	Description Opis	Impact on food waste valorisation Utjecaj na valorizaciju otpada od hrane	Future perspective / possible solution Buduća prespektiva/moguće rješenje
Data challenges. Podatkovni izazovi.	Data heterogeneity. Heterogenost podataka.	Food waste composition varies with origin, season, processing, and storage conditions. Sastav otpada od hrane varira ovisno o podrijetlu, sezoni, obradi i uvjetima skladištenja.	Reduces accuracy and reproducibility of machine learning models. Smanjuje točnost i ponovljivost modela strojnog učenja.	Development of standardised datasets and harmonised analytical protocols. Razvoj standardiziranih skupova podataka i usklađenih analitičkih protokola.
	Limited data availability. Ograničena dostupnost podataka.	Lack of comprehensive databases for agro-industrial residues and bioactive compounds. Nedostatak sveobuhvatnih baza podataka za agroindustrijske ostatke i bioaktivne spojeve.	Restricts development of robust predictive models. Ograničava razvoj robusnih prediktivnih modela.	Creation of open-access international databases. Izrada međunarodnih baza podataka otvorenog pristupa.
	Poor data quality. Loša kvaliteta podataka.	Incomplete, noisy, or inconsistent datasets. Nepotpuni, šumoviti ili nekonzistentni skupovi podataka.	Decreases reliability of AI-based optimisation systems. Smanjuje pouzdanost optimizacijskih sustava temeljenih na umjetnoj inteligenciji.	Improved data preprocessing and validation strategies. Poboljšane strategije predobrade i validacije podataka.
Technological limitations. Tehnološka ograničenja	High equipment cost Visoka cijena opreme.	Advanced sensors, IoT systems, and analytical instruments are expensive. Napredni senzori, IoT sustavi i analitički instrumenti su skupi.	Limits adoption by small- and medium-sized enterprises. Ograničava primjenu od strane malih i srednjih poduzeća.	Development of low-cost and portable sensing technologies. Razvoj jeftinih i prijenosnih tehnologija senzora.
	Infrastructure limitations. Ograničenja infrastrukture.	Insufficient digital infrastructure, cloud systems, and automation facilities. Nedovoljna digitalna infrastruktura, cloud sustavi i objekti za automatizaciju.	Restricts implementation in developing regions. Ograničava implementaciju u regijama u razvoju.	Investment in smart manufacturing infrastructure. Ulaganje u pametnu proizvodnu infrastrukturu.
	Integration complexity. Složenost integracije.	Difficulty integrating digital tools with existing industrial processes. Teškoće u integraciji digitalnih alata s postojećim industrijskim procesima.	Slows industrial digital transformation. Usporava industrijsku digitalnu transformaciju.	Development of user-friendly and modular digital platforms. Razvoj jednostavnih za korištenje i modularnih digitalnih platformi.
Machine learning limitations. Ograničenja strojnog učenja modela podataka.	Model overfitting. Pretjerano prilagođavanje.	ML models may perform well on training data but poorly on new datasets. ML model može dobro funkcionirati na podatcima za obuku, ali loše na novim skupovima.	Reduces practical industrial applicability. Smanjuje praktičnu industrijsku primjenjivost.	Use of larger datasets and cross-validation approaches. Korištenje većih skupova podataka i pristupa unakrsne validacije.

Table 3 – (continued)
Tablica 3 – (nastavak)

Category Kategorija	Key issue Ključni problem	Description Opis	Impact on food waste valorisation Utjecaj na valorizaciju otpada od hrane	Future perspective / possible solution Buduća prespektiva/moguće rješenje
Machine learning limitations. Ograničenja strojnog učenja modela podataka.	Lack of interpretability Nedostatak interpretabilnosti.	Some AI models operate as "black boxes". Neki AI modeli funkcioniraju kao "crne kutije".	Reduces trust among regulators and manufacturers. Smanjuje povjerenje među regulatorima i proizvođačima.	Development of explainable AI (XAI) systems. Razvoj objašnjivih AI (XAI) sustava.
	Need for expert knowledge. Potreba za stručnim znanjem.	ML implementation requires computational and data science expertise. Implementacija ML-a zahtijeva računalnu i podatkovnu znanost.	Limits adoption in traditional food industries. Ograničava primjenu u tradicionalnoj prehrambenoj industriji.	Interdisciplinary training and collaboration. Interdisciplinarna obuka i suradnja.
Industrial challenges. Industrijski izazovi.	Resistance to technological change. Otpor tehnološkim promjenama.	Traditional industries may prefer empirical methods. Tradicionalne industrije mogu preferirati empirijske metode.	Delays implementation of digital technologies. Odgađa implementaciju digitalnih tehnologija.	Demonstration of economic and operational benefits. Demonstracija ekonomskih i operativnih koristi.
	High initial investment. Visoka početna ulaganja.	Automation and AI systems require substantial financial resources. Automatizacija i sustavi umjetne inteligencije zahtijevaju značajna financijska sredstva.	Economic barrier for industrial adoption. Ekonomska prepreka za industrijsku primjenu.	Government incentives and public–private partnerships. Vladini poticaji i javno-privatna partnerstva.
	Scale-up difficulties. Poteškoće s povećanjem opsega.	Laboratory-scale digital solutions may not directly translate to industrial scale. Digitalna rješenja laboratorijskih razmjera možda se neće izravno prenijeti na industrijsku razinu.	Limits commercialisation potential. Ograničava potencijal komercijalizacije.	Pilot-scale validation and industrial simulation models. Validacija pilot-razmjera i industrijski simulacijski modeli.
Regulatory challenges. Regulatorni izazovi.	Food safety compliance. Usklađenost sa sigurnošću hrane.	Functional ingredients from waste streams must meet strict regulations. Funkcionalni sastojci iz tokova otpada moraju ispunjavati stroge propise.	Delays commercialisation of products. Odgađa komercijalizaciju proizvoda.	Development of standardised safety assessment protocols. Razvoj standardiziranih protokola za procjenu sigurnosti.
	Traceability requirements. Zahtjevi za sljedivost.	Need for transparent monitoring of raw materials and processing conditions. Potreba za transparentnim praćenjem sirovina i uvjeta prerade.	Increases complexity of production systems. Povećava složenost proizvodnih sustava.	Blockchain-based traceability systems. Sustavi sljedivosti temeljeni na "blockchain" tehnologiji.

Table 3 – (continued)
Tablica 3 – (nastavak)

Category Kategorija	Key issue Ključni problem	Description Opis	Impact on food waste valorisation Utjecaj na valorizaciju otpada od hrane	Future perspective/ possible solution Buduća prespektiva/moguće rješenje
Future perspective. Buduća perspektiva.	Artificial intelligence integration. Integracija umjetne inteligencije.	AI-driven predictive systems for process optimisation. Prediktivni sustavi vođeni umjetnom inteligencijom za optimiranje procesa.	Improved efficiency and reduced resource waste. Poboljšana učinkovitost i smanjeno rasipanje resursa.	Fully automated smart biorefineries. Potpuno automatizirane pametne biorafinerije.
	Digital twin technology. Tehnologija digitalnih blizanaca.	Virtual simulation of extraction and production systems. Virtualna simulacija sustava ekstrakcije i proizvodnje.	Real-time optimisation and reduced operational costs. Optimiranje u stvarnom vremenu i smanjeni operativni troškovi.	Expansion of digital twin applications in food industries. Proširenje primjene digitalnih blizanaca u prehrambenoj industriji.
	Blockchain technology. Blockchain tehnologija.	Transparent and secure data management systems. Transparentni i sigurni sustavi upravljanja podatcima.	Enhanced traceability and consumer trust. Poboljšana sljedivost i povjerenje potrošača.	Integrated blockchain-IoT food supply systems. Integrirani "blockchain-IoT" sustavi opskrbe hranom.
	Precision nutrition. Precizna prehrana.	Personalised functional food formulation using AI. Personalizirano formuliranje funkcionalne hrane korištenjem umjetne inteligencije.	Development of customised health-promoting foods. Razvoj prilagođene hrane koja promiče zdravlje.	AI-guided personalised nutrition platforms. Platforme za personaliziranu prehranu vođene umjetnom inteligencijom.
	Advanced biotechnology. Napredna biotehnologija.	Integration of synthetic biology and precision fermentation. Integracija sintetičke biologije i precizne fermentacije.	Production of novel functional ingredients. Proizvodnja novih funkcionalnih sastojaka.	Sustainable bio-based food manufacturing. Održiva proizvodnja hrane na biološkoj bazi.
	Interdisciplinary collaboration. Interdisciplinarna suradnja.	Cooperation among food scientists, engineers, and data scientists. Suradnja među znanstvenicima za rezvoj prehrambenih proizvoda, inženjerima i znanstvenicima podataka.	Accelerates technological innovation. Ubrzava tehnološke inovacije.	Global collaborative research networks. Globalne mreže za suradnička istraživanja.
	Circular bioeconomy implementation. Implementacija kružnog biogospodarstva.	Valorisation of food waste into high-value products. Valorizacija otpada od hrane u visokovrijedne proizvode.	Reduced environmental burden and increased sustainability. Smanjeno opterećenje okoliša i povećana održivost.	Fully integrated circular food production systems. Potpuno integrirani sustavi kružne proizvodnje hrane.

data acquisition, predictive modelling, process simulation, and optimisation during process development and scale-up. Furthermore, future optimisation strategies should simultaneously consider multiple objectives, including recovery yield, product quality and functionality, energy and resource consumption, environmental impact, and economic performance. Finally, combining digital and ML-based optimisation with pilot-scale validation, life-cycle assessment, and techno-economic analysis will be essential for translating laboratory-scale developments into industrial applications. The convergence of these research directions could facilitate the transition from individual digital applications toward predictive, adaptive, and economically viable smart biorefineries for food waste valorisation.

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SAŽETAK

Digitalizacija valorizacije otpada od hrane: primjena alata strojnog učenja u optimiranju sastava funkcionalnog prehrambenog proizvoda

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Otpad od hrane predstavlja značajan okolišni, gospodarski i društveni izazov na globalnoj razini. Prijelaz s konvencionalnih pristupa gospodarenju otpadom prema konceptima kružnog biogospodarstva potaknuo je razvoj inovativnih strategija valorizacije otpada od hrane usmjerenih na oporabu visokovrijednih spojeva, funkcionalnih sastojaka, biogoriva i drugih proizvoda dodane vrijednosti. Nedavni napredak digitalnih tehnologija znatno je unaprijedio učinkovitost i održivost tih procesa. Ovaj pregledni rad daje pregled suvremenih pristupa valorizaciji otpada od hrane, uključujući biološke, kemijske i fizikalne metode te ističe ulogu digitalnih alata u poboljšanju procesnih performansi i razvoju proizvoda. Poseban naglasak stavljen je na primjenu metoda strojnog učenja u optimiranju funkcionalnih prehrambenih proizvoda formuliranih od sastojaka dobivenih iz otpada od hrane. Suvremeni digitalni sustavi integriraju podatke prikupljene naprednim analitičkim metodama, sustavima Interneta stvari (IoT) i senzorskim tehnologijama, omogućujući praćenje procesa u stvarnom vremenu i donošenje odluka temeljenih na podatcima. Modeli strojnog učenja, poput umjetnih neuronskih mreža, strojeva potpornih vektora, slučajnih šuma i analize glavnih komponenti, omogućuju predviđanje kvalitete proizvoda, optimiranje procesnih uvjeta i određivanje optimalnih formulacija sastojaka. Dodatno, programske platforme kao što su Python, MATLAB, Aspen Plus i KNIME podržavaju modeliranje, simulaciju, vizualizaciju i optimiranje procesa valorizacije otpada od hrane. Unatoč značajnom potencijalu digitalizacije, izazovi povezani s kvalitetom podataka, tehnološkom infrastrukturom, interpretabilnošću modela, ekonomskom isplativošću i regulatornim zahtjevima i dalje su prepreke široj industrijskoj primjeni. Integracija digitalnih tehnologija i valorizacije otpada od hrane pruža značajne mogućnosti za povećanje učinkovitosti uporabe resursa, smanjenje utjecaja na okoliš te razvoj održivih i inovativnih prehrambenih sustava.

Ključne riječi

Valorizacija otpada od hrane, strojno učenje, funkcionalna hrana, digitalizacija, kružno biogospodarstvo

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