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Review Article

A Literature Review on Machine Learning in The Food Industry

Furkan Açıkgöz *

Res. Assist., Department of Economic, Faculty of Political Sciences, Sakarya University, Sakarya, Turkiye, furkanacikgoz@sakarya.edu.tr

Leyla Zeynep Verçin

M.Sc., Istanbul University, Istanbul, Turkiye, leylavercinn@gmail.com

Gamze Erdoğan

M.Sc., Department of Industrial Engineering, Faculty of Management, Istanbul Technical University, Istanbul, Turkiye, erdogang17@itu.edu.tr

* Sakarya Üniversitesi, Siyasal Bilgiler Fakültesi, Esentepe Kampüsü, 54187, Sakarya, Türkiye

ABSTRACT

Machine Learning (ML) has become widespread in the food industry and can be seen as a great opportunity to deal with the various challenges of the field both in the present and near future. In this paper, we analyzed 91 research studies that used at least two ML algorithms and compared them in terms of various performance metrics. China and USA are the leading countries with the most published studies. We discovered that Support Vector Machine (SVM) and Random Forest outperformed other ML algorithms, and accuracy is the most used performance metric.

Keywords: Machine Learning, Food, Food Industry, Classification, Support Vector Machine

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1. Introduction

Internet of Things (IoT), robotics, and Artificial Intelligence (AI), including Machine Learning (ML), Deep Learning, and Natural Language Processing, are the most emerging and trending technologies of the fourth Industrial revolution in the food industry. According to the World Economic Forum (WEF, 2020), AI adoption in the industry is 62 percent. Just as mechanization created deep-scaled changes in agriculture in the past, artificial intelligence will lead to a radical transformation in subsectors of the food industry today.

The term "Food industry" involves producers, distributors, retailers, and restaurants as its main stakeholders aiming to reduce costs and provide customers with more quality and safe goods and services. Here are examples of how food industry stakeholders use AI and ML technologies. Producers use them for protecting crops from weeds (Blue River Tech), analyzing soil (PEAT), web-based irrigation (Hortau Inc), weather prediction (aWhere), and analyzing crop genes (Benson Hill). Distributors use AI for doing more accurate sorting and classification (TOMRA), predicting decay and shelf-life of the food products (Savormetrics), identification of food fraud, improving hygiene conditions and food safety (KanKan, AgroKnow), optimizing supply-chain management (Symphony Retail AI). Retailers and restaurants use AI for food serving, inventory management, creating new recipes (doing Lab), and analyzing their customer's experience (Say2eat) (Cas Proffitt, 2017; Kovalenko, 2021; Insights, 2022). The use of AI in the food industry will enable companies to cope with the main challenges of the sector, such as food losses and food waste, which cause substantial economic loss, growing demand due to increasing world population, drought expectations by reason of climate change, etc., and so it will ensure a more efficient, healthy, and sustainable industry for all stakeholders (Kwasek, 2012; Sadiku et al., 2019).

Artificial intelligence encompasses various subdomains, with machine learning being one of them. ML is utilized for diverse purposes like classification, prediction, and clustering, and it can be broken down into three categories: supervised, unsupervised, and reinforcement learning. Supervised learning is used to predict the output from other variables in a dataset. Unsupervised learning does not have an output variable to be predicted. It is used to understand the dataset better, discover patterns inside data, and make classifications (Boehmke & Greenwell, 2020). Reinforcement learning means learning from the environment under iterative conditions (Ramasubramanian & Singh, 2019).

Different kinds of literature review articles focus on the applications of deep learning and machine learning in the food industry and its subsectors. Distinctly, we have analyzed 91 papers, including journal articles and conference proceedings, using multi-algorithm in the food industry for various tasks such as food classification, quality control, food processing, prediction, customer experience, food safety, etc.

This article consists of five sections. The following section outlines the food industry and the utilization of machine learning within it, organized into three distinct sub-sections. The third chapter describes ML algorithms and summarizes the relevant literature. The study's methodology, selection criteria of the studies, and findings are presented in the fourth chapter. The final section discusses the study's findings and explains how the study contributed to the industry and the literature.

2. Overview of the Food Industry

2.1. Quality Control

The food industry took its place among fast-paced sectors. When the speed of the industry reached the point where human labor could no longer be sufficient, automated solutions came to fill this gap. New technologies are going head-to-head with the need for high-level operations; the requirements and complexity of the products are also broadening and diversifying, and as a consequence of this complexity, the inspection stage needs new developments to provide production sustainability (Schmitt et al., 2020).

According to the Food and Agriculture Organization of the United Nations (2022), around 14% of the food produced worldwide is wasted between harvest and retail. This number is lower yearly due to better inspection processes provided by technological development in the quality control field. It is crucial to attain the undamaged output in the final stage of the product, and companies need to develop their work into stocking high-level products to become lucrative businesses in the long run and to confront competitors, as Schmitt et al. (2020) argued. While stocking products, companies need to prioritize food quality, which is where the practicality of machine learning applications comes into play.

Image processing techniques often replace humans for quality inspection: such methods are non-invasive, accurate, and cost-efficient. Integrated ML techniques can enhance visual analysis for automated sorting (Tongcham et al., 2020). Quality inspection, as the definition infers, assesses the product by its color, size, ripeness, rottenness, contamination, and potential threat to the consumers. Common classifiers of color classification are ANN and SVM (De-la-Torre et al., 2019), although KNN is also provided successful results (Li et al., 2014). Regarding ripeness detection, support vector models become the primary classifier for firmness prediction (Castro et al., 2019; Cho et al., 2020). On the other hand, for size-based detection Random Forest (RF) is favored due to its success in pointing the distinctness (Vidyarthi et al., 2020); KNN is another useful model to predict the correct product stage by size (Rady & Adedeji, 2020). Food contamination can be easily detected when the PCA-kNN model is utilized (Bonifazi et al., 2021). Finally, Quatrini et al. (2020) comment on the high performance of Random forests (or random decision forests) while distilling the unsafe products in production.

The most used algorithms to conduct food inspections for the seemingness of a shape, color, maturity, or size are Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbours (KNN) algorithm; however, Jiménez-Carvelo et al. (2019) argue SVM is the most commonly used model among three for enhanced performance.

2.2. Food Classification & Food Processing

After harvesting, raw material is stored, processed, turned into products, packaged, and distributed to the market. Food processing is a post-harvesting activity that creates added value to the food & beverage before its marketing. From the beginning of the twentieth century, mass manufacturing and, because of its effect, consumption of processed food products have become widespread (Moubarac et al., 2014). Due to its complex nature, food processing takes much time and effort, needs skilled employees, and requires clean, zero-touch phases and high accuracy in all steps. Machine learning applications combined with the human workforce and computer vision provide a considerable benefit in food processing in line with the needs of the food industry. Some examples of these needs are reducing the time required to process food, averting food loss, providing more safe and hygienic conditions, increasing the accuracy of all decision-making, and improving customer experience (WizataTeam, 2021).

Food processing is also a vital phase to avert food loss which is a considerable challenge to be dealt with in the industry. According to World Economic Forum (WEF, 2019), 14%-21% of production for fruits and vegetables is lost during processing in developing countries. Mistakes made in food processing also cause enormous costs for developed countries. Due to the mishaps, companies sometimes resort to the high-cost but obligatory "recall" method. Recent recall examples such as Hallmark/Westland Meat Packing, Peanut Corporation of America, and Wright County/Hillandale Farms happened in developed countries and cost these companies billions of dollars. It can be clearly said that food processing must be conducted meticulously because of its proximity to other subdomains of the industry, such as food safety and food marketing.

The papers related to ML applications in food processing have been handled together with food quality control, food safety, and food marketing, and most of the studies we analyzed used ML algorithms for classification and prediction. Here are some examples; Erban et al. (2019) used ML for the verification of food authentication; Vidyarthi et al. (2020) combined ML with image processing to measure the size and mass of whole raw almonds; Ribeiro et al. (2009) used it to predict the organoleptic parameters from the chemical parameters of the vinification process.

2.3. Marketing and Customer Experience

One of the most complex scenarios in which AI and ML are applied is within business areas where human input is indispensable (Nyce, 2007). Both customer experience and predictions are vital parts of a business that inevitably have human elements. The volatility and subjectivity of humans have always made it harder for the machine to process and reach a definitive conclusion in both subfields.

In the context of the food industry, one of the first uses of artificial intelligence in customer experience is undoubtedly pattern recognition. To gain feedback from users, more often than not, offering incentives would yield a greater amount of data than the alternative (Min et al., 2020). That is how recommendation applications are born. Many food ordering applications tend to use these recommendation algorithms in the background. The scope of these recommendations can range from showing similar restaurants after a successful order to offering new recipe recommendations after classifying the individuals' food palettes, like CHOPCHOP or HALLA, in the particular case of picky eaters (Cas Proffitt, 2017).

One of the most significant disadvantages of traditional prediction methods used in the industry is their dependency on previously acquired data (Taylor & Letham, 2018). While processing willingly and consciously given data is an obstacle on its own, like every other product, this approach only scratches the surface of what the customers think (Miles & Scaife, 2003). The reviews can be biased; for example, if the restaurant offers a coupon to everyone, that leaves a five-star rating. The in-depth analysis of customers' real thoughts about a food product can be improved if more data is obtained by various means. Say2Eat uses data across all platforms, text, Facebook (consequentially WhatsApp), and Amazon Echo, to provide its clients with a thorough customer experience analysis (Say2eat, 2017).

3. Machine Learning Algorithms and Literature Review

In this section, we briefly describe ML algorithms used in food industry applications, their advantages and disadvantages in Table 1 below.

Name	Description	Advantage	Disadvantage
Support Vector Machine (SVM)	SVM divides the data in two in a homogeneous way with a flat boundary called a hyperplane.	1- Can be used for classification or prediction purposes 2- Not overly influenced by noisy data 3- High accuracy	1- It requires testing various combinations of kernels and model parameters 2- complex black-box model that is difficult to interpret
Multivariate Regression	The primary usage of regression is to define the relationship of a single numeric valuable with at least one independent variable.	1- Common approach for modeling. 2- Provides estimates of both the strength and size of the relationships among features and the outcome	1- It requires strong assumptions 2- It does not handle missing data. 3- Categorical data requires extra processing.
Logistic Regression	Primarily used for prediction, descriptive studies, and testing theoretical hypotheses, logistic regression differs with giving binary target variables.	1- Simple to operate. 2- Easy calculation. 3- Small storage resources. 4- Option to obtain discrete or continuous results.	Poor fitness and precision.
Neural Network	Neural networks are capable of learning from all sorts of datasets without needing assumptions.	Strong nonlinear fitting ability, simple learning rules, and strong robustness with memory ability.	1- Unable to explain the reasoning process and basis. 2- Sensitive to initial values.
Random Forest (RF)	RF adds diversity to the decision tree models by combining fundamental principles of bagging with random feature selection.	1- Can handle noisy or missing data as well as categorical or continuous features. 2- Selects only the most important features.	1- Unlike a decision tree, the model is not easily interpretable. 2- It may require some work to tune the model to the data.
K-Nearest Neighbour (KNN)	Nearest neighbor classifiers group unlabeled examples with similar labeled examples.	Despite the simplicity of this idea, nearest-neighbor methods are extremely powerful.	1- Does not produce a model 2- Requires selection of an appropriate k.
K-means	K-means aim to minimize the effect of random chance and get closer to the optimal clustering solution.	1- Highly flexible and can be adapted with simple adjustments to address nearly all its shortcomings. 2- Performs well for real-world use cases.	1- Requires a reasonable guess as to how many clusters naturally exist in the data. 2- Not ideal for non-spherical clusters
Naive Bayes	Naïve Bayes applies the Bayes theorem as a classification solution as a simple and well-known alternative.	1- Simple, fast, and very effective. 2- Does well with noisy and missing data. 3- Even if assumptions are violated, it still performs well.	1- It is quite difficult to meet assumptions. 2- Estimated probabilities are less reliable than the predicted classes.

Name	Description	Advantage	Disadvantage
Gradient Boosting (GM)	GBMs build an ensemble of shallow trees in sequence with each tree learning and improving on the previous one.	1- GB has superior robustness. 2- It is less likely to be influenced by the scale of training sets and outliers.	Overfitting.
Decision Tree	The decision trees model provides a relation between features and possible outcomes.	1- It can handle numeric or nominal features and missing data. 2- Suitable small and large datasets.	1- Decision tree models are often biased toward splits on many-level features. 2- It is easy to overfit or underfit the model.
Principal Component Analysis (PCA)	The main use case of PCA is to reduce the dimensions of the dataset.	PCA can reduce dimensionality without losing taste and value.	It does not allow classifying and assigning a class to each sample.
Discriminant Analysis	It can be used as a dimensionality reduction technique in the pre-processing step for ML.	Even if its assumptions are violated, LDA works very well.	LDA may miss complex nonlinear relationships since assuming linearity.

Source: (Lantz, 2015; Lewis, 2017; Cui et al., 2018; Jiménez-Carvelo et al., 2019; Ramasubramanian & Singh, 2019; Boehmke & Greenwell, 2020; Ni et al., 2020)

Table 1. Descriptions of Machine Learning Algorithms

In the existing literature, review articles discuss the use of machine learning in the food industry. Zhou et al. (2019) surveyed dozens of articles utilizing deep learning in food recognition, calorie estimation, quality detection of fruits, vegetables, meat, aquatic products, food supply chain, and food contamination. Researchers note that DL yields better outcomes than techniques such as manual feature extraction and conventional ML and emphasize that DL is a promising food quality and safety method. In their study, Jiménez-Carvelo et al. (2019) conducted a comprehensive analysis of 79 research papers focusing on the application of ML techniques in the domains of food quality and authentication. The researchers observed that Support Vector Machine (SVM), Classification and Regression Tree (CART), and Random Forest (RF) consistently demonstrated highly favorable outcomes in both fields compared to conventional methods. These findings underscore the effectiveness and potential of SVM, CART, and RF algorithms as powerful tools for addressing food quality and authentication challenges when employing ML approaches. Ni et al. (2020) analyzed 123 studies that utilized ML techniques in supply chain management, an essential part of the food industry, between 1998 and 2018. The articles were sourced from reputable databases such as Emerald Insight, IEEE Xplore, Scopus, Science Direct, Wiley, Springer, and Google Scholar. The most used algorithms were Neural Networks, SVM, and Logistic Regression. Sakinah Shaeeali et al. (2020) conducted a comprehensive review of 53 research studies that applied ML techniques to customer analytics in the food industry, utilizing data sourced from social media platforms. Their results indicate that customers assess their opinions concerning 28 business aspects. The authors categorized these 28 factors into four main groups: experience, food quality, service quality, and quality control. Saha and Manickavasagan (2021) reviewed more than 50 studies in the context of food quality assessment. They provided a comprehensive review of the use of various ML techniques for the analysis of hyperspectral images. The researchers highlight ML techniques enable rapid and accurate analysis of hyperspectral food images, leading to robust models for classification and regression. Sood and Singh (2021) investigated 39 studies that applied computer vision and machine learning-based techniques in food security. They intend to address various challenges, including food scarcity, declining quality, food wastage, product loss, and the constraints posed by limited natural resources. They observe that DL produced superior outcomes to traditional image processing methods as a result. Furthermore, they found the most used ML method is SVM after DL techniques (CNN, Transfer Learning Model, Alexnet and VGG16). Bhagya Raj and Dash (2022) investigated the use of artificial neural networks (ANNs), a machine learning technique, in food engineering. ANNs have the capacity to map nonlinear relationships without the need for prior knowledge and predict outcomes even when given insufficient data. According to the authors, ANN is a novel method in the field of food processing, and it stands out in the areas such as extraction, extrusion, drying, filtration, canning, fermentation, baking, dairy processing, and quality evaluation.

This study diverged from existing literature by prioritizing research that employed multiple machine learning algorithms within the food industry. This approach facilitated a broader algorithmic comparison within a limited study pool. A total of 93 studies were examined, and the findings are outlined in the subsequent section.

4. Methodology and Data Analysis

4.1 Methodology

Our search was constrained to publications released between 2005 – 2021, encompassing the latest field advancements. Our primary sources are Google Scholar and Scopus, distinguished academic databases known for their extensive scientific literature coverage. In total, we have gathered 91 studies, including 67 journal articles, 22 conference papers, and two dissertations that used multiple machine learning algorithms and compared them in terms of various parameters within the specified time frame. 72 of 91 studies are indexed in the Web of Science and Scopus indexes. While searching articles on Google Scholar and Scopus, specific keywords were initially employed. Our chosen keywords include: "machine learning in the food industry," "machine learning in food quality," "machine learning in customer experience," "machine learning in food security/safety," "machine learning in food processing," "machine learning multiple algorithms," and "machine learning in food classification." Subsequently, studies using these keywords in the title, abstract or among keywords were obtained and evaluated. Those that exclusively utilized a single machine learning algorithm or focused solely on deep learning were excluded from consideration. Instead, our focus remained on selecting and including research that employed multiple ML algorithms, allowing for the comparison of outcomes. These selected studies were then incorporated into our analysis.

The data in the research was gathered through manual compilation without employing any bibliometric software. The authors of the articles cross-checked the chosen studies to confirm their alignment with the selection criteria and to validate the accuracy of the information gathered from the articles. Graphical visualizations were generated utilizing MS Excel 2016.

4.2 Data Analysis

Figure 1 illustrates the publication years of reviewed articles and conference proceedings as graphed below. Despite the fact that we only looked at the studies that used multiple algorithms, it is clear from the graph that ML is being used more and more in the food industry. According to Figure 1, the first peak occurred after the

2008 crisis. The second peak, on the other hand, is observed post-2016. Similar findings are also evident in the studies by Ni et al. (2020) and Sakinah Shaeeali et al. (2020). According to Ni et al. (2020), the reason behind the first peak is the growing interest in the effectiveness of machines in decision-making processes after the 2008 crisis, as opposed to relying on humans. However, the second peak is attributed to AI's increasing popularity after 2016.

In contrast to our findings, the study conducted by Sood & Singh (2021) suggests a decline post-2016. In our opinion, the article's authors, the initial increase in the graph is attributed to efforts toward new decision-making processes following the 2008 crisis. The subsequent increases from 2012 onwards can be attributed to the resurgence of interest in machine learning due to the advent of the deep learning revolution. The increase post-2016 is linked to the popularity of AI technologies. The decline in 2021 could be attributed to several factors, such as the possibility that articles published in that year were not yet fully incorporated into the databases. Additionally, researchers might have shifted their focus towards COVID-related research during the pandemic, or it is also possible that the overall performance of the studies decreased.

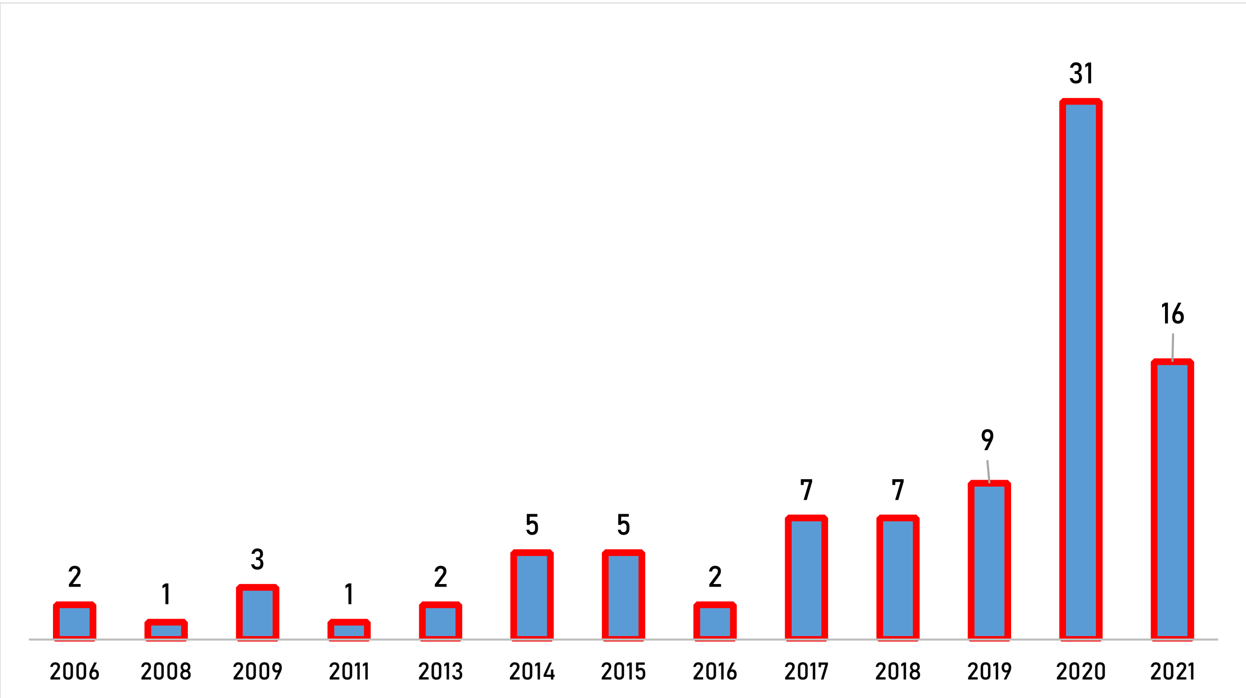

Figure 1. The publication years

We also visualized the authors' countries of the studies we examined in Figure 2. In this map, dark colors indicate countries that published more.

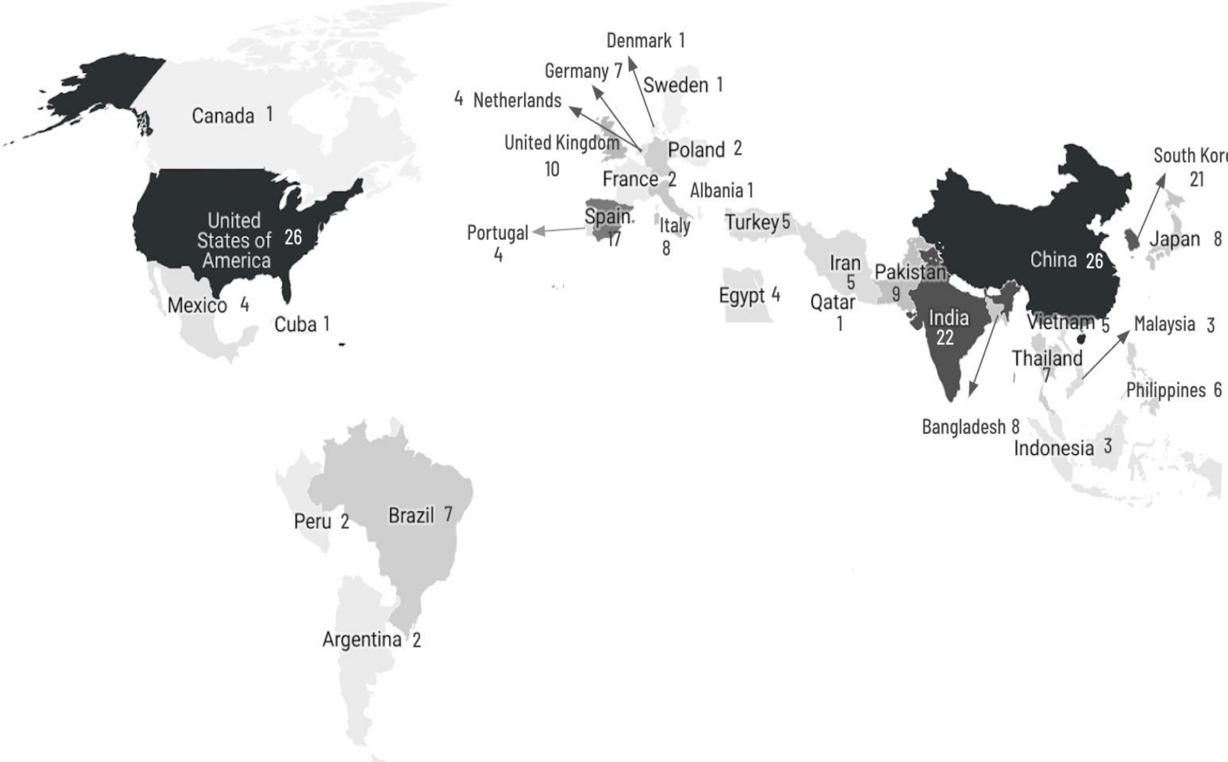

Figure 2. Map view

Within the studies we examined, the highest amount of research was conducted in the United States and China, contributing to 26 articles. Following this, India and South Korea had 22 and 21 articles, respectively. Spain is the fourth country with 17 research, and the UK comes after Spain with 10. The rest of the countries have less than ten published articles on ML applications in the food industry. This map's findings are largely supported by Martinho et al. (2022), who have studied countries by total link strength, finding USA and China to be almost twice as strong as the third country, Australia, which isn't logged in our study. The study also indicates that India and England are ranked among the five leading nations, aligning with our discoveries. Technological advancements and quality of life may explain the high number of studies in the USA and UK, while the population likely explains the reason behind China and India.

Figure 3 demonstrates the keywords of the reviewed studies according to the frequency of use. The most frequently preferred keywords by researchers are "machine learning," "support vector machine," "neural network," and "classification."

Figure 3. Featured keywords

The most studied item in the research for classification or prediction purposes are the ones that stand out in Figure 4 below. As it is shown, olive oil, wine, milk, meat, and restaurants review are leading. Milk and meat are perishable goods; they pose high health risks. Therefore, researchers have conducted many studies on them in order to minimize these risks.

Figure 4. Featured items

Our paper primarily aims to assess research employing multiple ML algorithms for diverse functions, including classification and prediction, within various subdomains of the food industry. In line with the paper's aim, we have depicted in Figure 5 below the algorithms most commonly utilized in the articles under our scrutiny. It is observed that SVM, Regression, and Random Forest algorithms stand out. Significantly, the prominence of SVM and RF algorithms is in line with the findings of Jiménez-Carvelo et al. (2019), Ni et al. (2020), and Saha and Manickavasagan (2021).

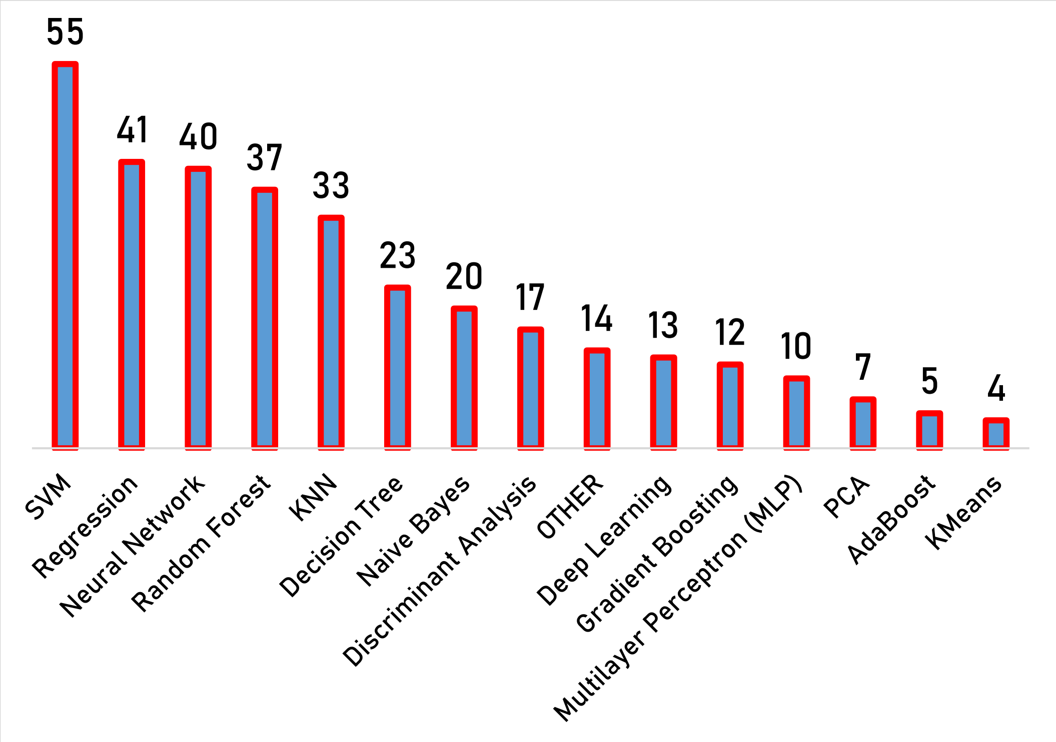

Figure 5. Most used algorithms

We also illustrated the winner algorithms that outperformed others in Figure 6. The following graph presents winner algorithms according to their frequency. The leading algorithms are support vector machine, random forest, and neural network algorithms. Although Regression, Neural Networks, Random Forest, and KNN have close usage frequency, random forest and neural networks stand out from the other two in terms of performance. SVM has shown outstanding performance, winning almost half of the studies in which it is used.

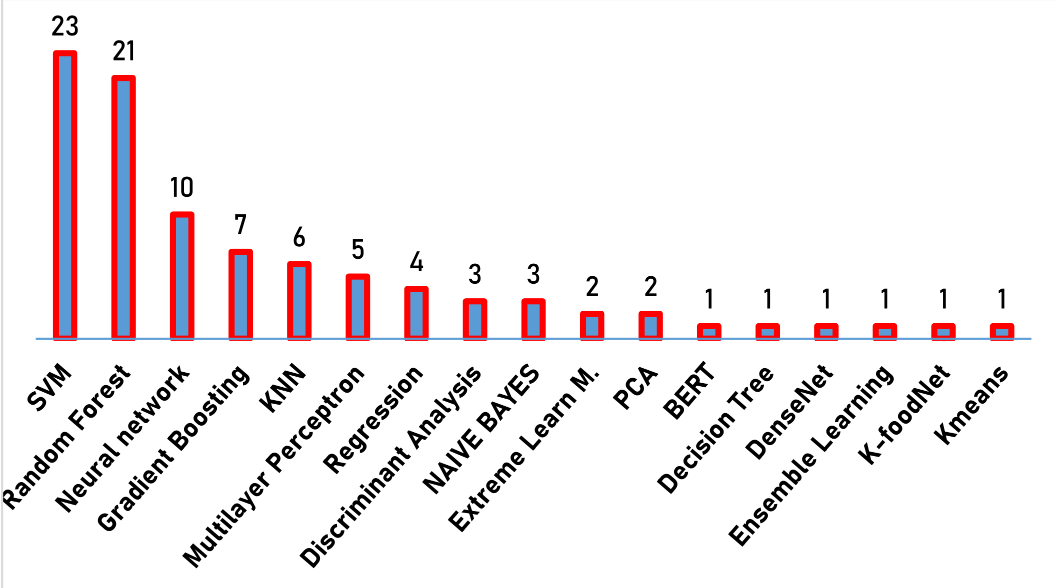

Figure 6. The frequency of the winner algorithms

As is known, various metrics are used to evaluate the performance of machine learning algorithms. Finally, we graphed the utilization frequency of performance metrics in Figure 7. The most preferred metrics are accuracy, recall, and specificity, respectively.

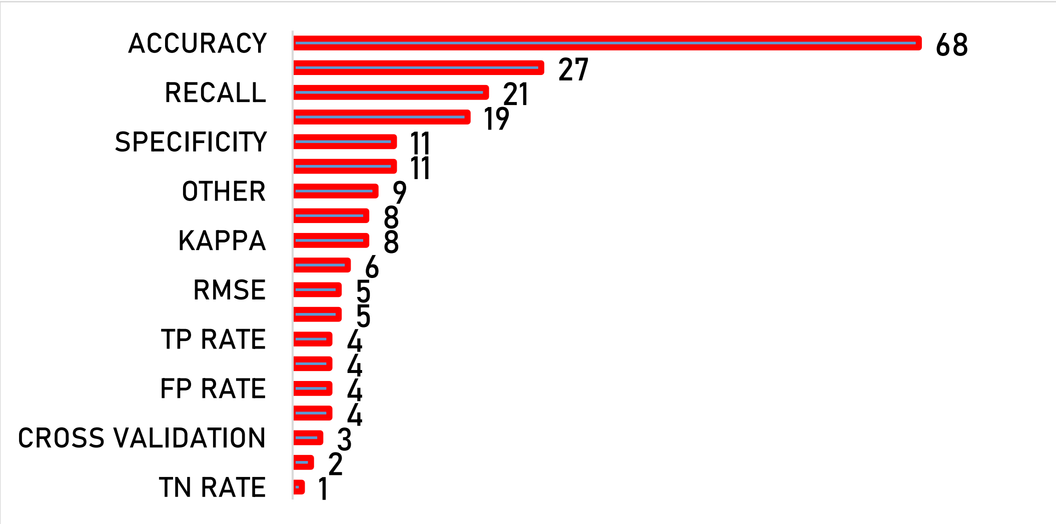

Figure 7. The frequency of the parameters used for comparison.

5. Discussion

Based on our study findings, an increase in the utilization of ML after 2008, 2012, and 2016 is evident. These findings align with the discoveries of Ni et al. (2020) and Sakinah Shaeeali et al. (2020). However, in the study by Sood & Singh (2021), which focuses on the field of food security and encompasses 39 works, a decline post-2016 is demonstrated. This divergence in results might stem from the smaller number of studies in their research, the specificity of their study to a particular sub-domain within the food industry, or disparities in our article selection criteria. In our study, the countries with the most contributions are the USA, China, India, South Korea, and Spain sequentially. Similarly, in Martinho et al.'s (2022) study, the top five include the

USA, China, and India. Ni et al. (2020) also have the USA, China, and Korea in their top five. The most frequently employed algorithms are SVM, Regression, and Neural Networks. The most successful algorithms, in order, are SVM, Random Forest, and Neural Networks. These findings align with the results of other studies in the literature (Jiménez-Carvelo et al., 2019; Ni et al., 2020; Bhagya Raj & Dash, 2022). According to our results, the most used comparison parameter is accuracy by a significant margin, followed by precision and recall.

6. Results

Similar to other sectors such as Finance, Logistics, and Manufacturing, Machine Learning can play a significant role in addressing fundamental challenges in the food industry. Existing literature demonstrates that integrating ML technologies into the food industry can provide solutions to the low-efficiency issue stemming from processes previously reliant on human effort in subfields such as food quality, food processing, food classification, food safety/security, and customer satisfaction. While the use of artificial intelligence is increasing in the industry, research focusing on the applications of machine learning algorithms in the food industry and its subfields continues to grow in the literature. At this point, literature review articles take on significance. Literature review studies are conducted to gain insights into the general trends of the existing literature amidst the rapidly growing body of research.

In this study, the authors first elucidate the utilization of machine learning in the food industry and its subfields. Subsequently, they introduce commonly employed ML algorithms within the food industry, discussing their advantages and disadvantages. The specific aim of the study, setting it apart from the existing literature, is to assess the literature by evaluating studies that employ multiple ML algorithms. This approach allows us to not only identify the best-performing algorithms but also to assess a greater variety of algorithms with fewer studies and enables us to compare these algorithms.

Our study demonstrates that SVM and Random Forest algorithms should be the primary choices for researchers in approaching problems within the food industry. SVM is robust in high-dimensional spaces and apt for complex datasets with multiple attributes. Its kernel trick handles nonlinear food industry data well. Random Forest is another key choice, excelling in accurate classifications crucial for precision-focused food applications. It also handles overfitting and large datasets effectively, which is ideal for agriculture and quality analysis.

In sum, it can be precisely said that ML holds a great potential in addressing many problems in the food industry from harvesting to marketing. ML-based solutions increase market efficiency and offer innovations to businesses. It is believed that the insights derived from this study will motivate companies to adopt ML in the food industry and will also provide benefits to researchers.

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References

Bhagya Raj, G. V. S., & Dash, K. K. (2022). Comprehensive study on applications of artificial neural network in food process modeling. Critical Reviews in Food Science and Nutrition, 62(10), 2756–2783. https://doi.org/10.1080/10408398.2020.1858398

Boehmke, B., & Greenwell, B. (2020). Hands-On Machine Learning with R. CRC Press - Taylor & Francis Group.

Bonifazi, G., Capobianco, G., Gasbarrone, R., & Serranti, S. (2021). Contaminant detection in pistachio nuts by different classification methods applied to short-wave infrared hyperspectral images. Food Control, 130, 108202. https://doi.org/10.1016/j.foodcont.2021.108202

Cas Proffitt. (2017). Top 10 Artificial Intelligence Companies Disrupting The Food Industry. Disruptor Daily. https://www.disruptordaily.com/top-10-artificial-intelligence-disrupting-food-industry/

Castro, W., Oblitas, J., De-La-Torre, M., Cotrina, C., Bazan, K., & Avila-George, H. (2019). Classification of Cape Gooseberry Fruit According to its Level of Ripeness Using Machine Learning Techniques and Different Color Spaces. IEEE Access, 7, 27389–27400. https://doi.org/10.1109/ACCESS.2019.2898223

Cho, B.-H., Koyama, K., Olivares Díaz, E., & Koseki, S. (2020). Determination of "Hass" Avocado Ripeness During Storage Based on Smartphone Image and Machine Learning Model. Food and Bioprocess Technology, 13(9), 1579–1587. https://doi.org/10.1007/s11947-020-02494-x

Cui, H., Huang, D., Fang, Y., Liu, L., & Huang, C. (2018). Webshell Detection Based on Random Forest–Gradient Boosting Decision Tree Algorithm. 2018 IEEE Third International Conference on Data Science in Cyberspace (DSC), 153–160. https://doi.org/10.1109/DSC.2018.00030

De-la-Torre, M., Zatarain, O., Avila-George, H., Muñoz, M., Oblitas, J., Lozada, R., Mejía, J., & Castro, W. (2019). Multivariate Analysis and Machine Learning for Ripeness Classification of Cape Gooseberry Fruits. Processes, 7(12), 928. https://doi.org/10.3390/pr7120928

Erban, A., Fehrle, I., Martinez-Seidel, F., Brigante, F., Más, A. L., Baroni, V., Wunderlin, D., & Kopka, J. (2019). Discovery of food identity markers by metabolomics and machine learning technology. Scientific Reports, 9(1), 9697. https://doi.org/10.1038/s41598-019-46113-y

Insights, S. (2022, January 31). 5 Top AI Startups impacting the Food Industry. StartUs Insights. https://www.startus-insights.com/innovators-guide/ai-startups-impacting-the-food-industry/

Jiménez-Carvelo, A. M., González-Casado, A., Bagur-González, M. G., & Cuadros-Rodríguez, L. (2019). Alternative data mining/machine learning methods for the analytical evaluation of food quality and authenticity – A review. Food Research International, 122, 25–39. https://doi.org/10.1016/j.foodres.2019.03.063

Kovalenko, O. (2021, July 23). Machine Learning and AI in the Food Industry. SPD Group. https://spd.group/machine-learning/machine-learning-and-ai-in-food-industry/

Kwasek, M. (2012). Threats to Food Security and Common Agricultural Policy. Economics of Agriculture, 59(4), 701–713.

Lantz, B. (2015). Machine learning with R: Discover how to build machine learning algorithms, prepare data, and dig deep into data prediction techniques with R (Second edition). Packt Publishing.

Lewis, N. D. (2017). Machine learning made easy with R: An intuitive step by step blueprint for beginners. AusCov.

Li, H., Lee, W. S., & Wang, K. (2014). Identifying blueberry fruit of different growth stages using natural outdoor color images. Computers and Electronics in Agriculture, 106, 91–101. https://doi.org/10.1016/j.compag.2014.05.015

Martinho, V. J. P. D., Cunha, C. A. D. S., Pato, M. L., Costa, P. J. L., Sánchez-Carreira, M. C., Georgantzís, N., Rodrigues, R. N., & Coronado, F. (2022). Machine Learning and Food Security: Insights for Agricultural Spatial Planning in the Context of Agriculture 4.0. Applied Sciences, 12(22), 11828. https://doi.org/10.3390/app122211828

Miles, S., & Scaife, V. (2003). Optimistic bias and food. Nutrition Research Reviews, 16(01), 3. https://doi.org/10.1079/NRR200249

Min, W., Jiang, S., & Jain, R. (2020). Food Recommendation: Framework, Existing Solutions, and Challenges. IEEE Transactions on Multimedia, 22(10), 2659–2671. https://doi.org/10.1109/TMM.2019.2958761

Moubarac, J.-C., Parra, D. C., Cannon, G., & Monteiro, C. A. (2014). Food Classification Systems Based on Food Processing: Significance and Implications for Policies and Actions: A Systematic Literature Review and Assessment. Current Obesity Reports, 3(2), 256–272. https://doi.org/10.1007/s13679-014-0092-0

Ni, D., Xiao, Z., & Lim, M. K. (2020). A systematic review of the research trends of machine learning in supply chain management. International Journal of Machine Learning and Cybernetics, 11(7), 1463–1482. https://doi.org/10.1007/s13042-019-01050-0

Nyce, C. (2007). Predictive Analytics White Paper (Insurance Institute of America, 9-10.). American Institute for CPCU - Insurance Institute of America. https://www.the-digital-insurer.com/wp-content/uploads/2013/12/78-Predictive-Modeling-White-Paper.pdf

Quatrini, E., Costantino, F., Di Gravio, G., & Patriarca, R. (2020). Machine learning for anomaly detection and process phase classification to improve safety and maintenance activities. Journal of Manufacturing Systems, 56, 117–132. https://doi.org/10.1016/j.jmsy.2020.05.013

Rady, A., & Adedeji, A. A. (2020). Application of Hyperspectral Imaging and Machine Learning Methods to Detect and Quantify Adulterants in Minced Meats. Food Analytical Methods, 13(4), 970–981. https://doi.org/10.1007/s12161-020-01719-1

Ramasubramanian, K., & Singh, A. (2019). Machine Learning Using R: With Time Series and Industry-Based Use Cases in R. Apress. https://doi.org/10.1007/978-1-4842-4215-5

Ribeiro, J., Neves, J., Sanchez, J., Delgado, M., Machado, J., & Novais, P. (2009). Wine Vinification prediction using Data Mining tools. Computing and Computational Intelligence. WSEAS, 78–85.

Sadiku, M. N. O., Musa, S. M., Ashaolu, T. J., & Roy G. Perry College of Engineering, Prairie View AandM University, Prairie View, Texas, United States. (2019). Food Industry: An Introduction. International Journal of Trend in Scientific Research and Development, Volume-3(Issue-4), 128–130. https://doi.org/10.31142/ijtsrd23638

Saha, D., & Manickavasagan, A. (2021). Machine learning techniques for analysis of hyperspectral images to determine quality of food products: A review. Current Research in Food Science, 4, 28–44. https://doi.org/10.1016/j.crfs.2021.01.002

Sakinah Shaeeali, N., Mohamed, A., & Mutalib, S. (2020). Customer reviews analytics on food delivery services in social media: A review. IAES International Journal of Artificial Intelligence (IJ-AI), 9(4), 691. https://doi.org/10.11591/ijai.v9.i4.pp691-699

Say2eat. (2017). Chatbots are Here to Stay. https://chatbotnewsdaily.com/chatbots-are-here-to-stay-46195401b734

Schmitt, J., Bönig, J., Borggräfe, T., Beitinger, G., & Deuse, J. (2020). Predictive model-based quality inspection using Machine Learning and Edge Cloud Computing. Advanced Engineering Informatics, 45, 101101. https://doi.org/10.1016/j.aei.2020.101101

Sood, S., & Singh, H. (2021). Computer Vision and Machine Learning based approaches for Food Security: A Review. Multimedia Tools and Applications, 80(18), 27973–27999. https://doi.org/10.1007/s11042-021-11036-2

Taylor, S. J., & Letham, B. (2018). Forecasting at Scale. The American Statistician, 72(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080

Tongcham, P., Supa, P., Pornwongthong, P., & Prasitmeeboon, P. (2020). Mushroom spawn quality classification with machine learning. Computers and Electronics in Agriculture, 179, 105865. https://doi.org/10.1016/j.compag.2020.105865

United Nations. (2022). Food Loss and Waste Reduction. United Nations; United Nations. https://www.un.org/en/observances/end-food-waste-day

Vidyarthi, S. K., Tiwari, R., & Singh, S. K. (2020). Stack ensembled model to measure size and mass of almond kernels. Journal of Food Process Engineering, 43(4). https://doi.org/10.1111/jfpe.13374

WEF. (2019). Innovation with a Purpose: Improving Traceability in Food Value Chains through Technology Innovations (System Initiative on Shaping the Future of Food). World Economic Forum. http://www3.weforum.org/docs/WEF_Traceability_in_food_value_chains_Digital.pdf

WEF. (2020). Future of Jobs Report 2020. World Economic Forum. https://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf

WizataTeam. (2021). How the Food Industry Can Benefit From AI. https://www.wizata.com/knowledge-base/how-the-food-industry-can-benefit-from-ai

Zhou, L., Zhang, C., Liu, F., Qiu, Z., & He, Y. (2019). Application of Deep Learning in Food: A Review. Comprehensive Reviews in Food Science and Food Safety, 18(6), 1793–1811. https://doi.org/10.1111/1541-4337.12492