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Artificial intelligence and machine learning approaches in composting process: A review

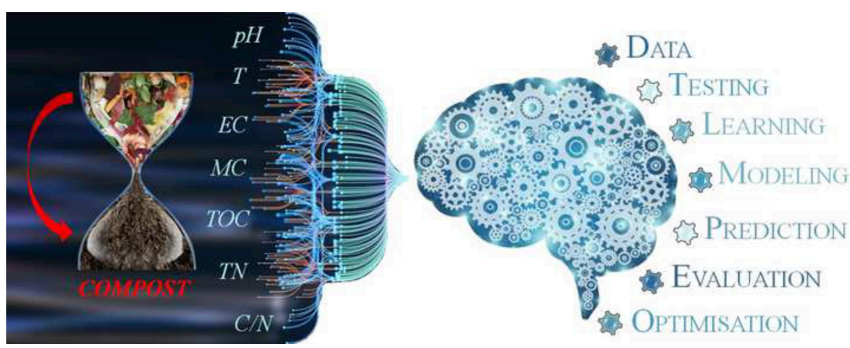
Fulya Aydın Temel [a,*], Ozge Cagcag Yolcu [b], Nurdan Gamze Turan [c]

[a] Department of Environmental Engineering, Faculty of Engineering, Giresun University, Giresun 28200, Turkey
[b] Department of Statistics, Faculty of Sciences and Arts, Marmara University, İstanbul 34722, Turkey
[c] Department of Environmental Engineering, Faculty of Engineering, Ondokuz Mayıs University, Samsun 55200, Turkey

HIGHLIGHTS

- Machine learning algorithms has a great potential for modeling of composting.
- Machine learning have shortcomings as well as superior features in composting.
- The proper metric is a key for evaluating the algorithm as a realistic.
- Complexity of composting can limit accurate prediction by experiment or theory.

GRAPHICAL ABSTRACT



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ABSTRACT

Studies on developing strategies to predict the stability and performance of the composting process have increased in recent years. Machine learning (ML) has focused on process optimization, prediction of missing data, detection of non-conformities, and managing complex variables. This review investigates the perspectives and challenges of ML and its important algorithms such as Artificial Neural Networks (ANNs), Random Forest (RF), Adaptive-network-based fuzzy inference systems (ANFIS), Support Vector Machines (SVMs), and Deep Neural Networks (DNNs) used in the composting process. In addition, the individual shortcomings and inadequacies of the metrics, which were used as error or performance criteria in the studies, were emphasized. Except for a few studies, it was concluded that Artificial Intelligence (AI) algorithms such as Genetic algorithm (GA), Differential Evaluation Algorithm (DEA), and Particle Swarm Optimization (PSO) were not used in the optimization of the model parameters, but in the optimization of the parameters of the ML algorithms.

1. Introduction

Organic wastes are commonly disposed of by anaerobic digestion, composting, and thermal methods. Among these, composting is preferred because of its low investment and operation costs, greater social and environmental benefits, and generation of a marketable final product. Composting is a biochemical process that converts organic waste into a stable and safe product that can be used as a substrate and

* Corresponding author.

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nutrient source for plant growth. The maturation process is critical to producing high-quality compost. The maturity index is an evaluation procedure used for the degree of the decomposition of feedstocks and the completeness of composting process. It includes specific tests that provide the greatest assurance for the producer and user. Compost must pass two or more of these tests for maturity. Based on these test results, composts are categorized as very mature, mature, and immature. Mature compost is beneficial for plants while immature compost can inhibit seed germination, and root and seedling growth due to including high concentrations of volatile fatty acids, free ammonia, or other toxic compounds. Immature compost can become anaerobic and release odor. Also, immature compost can cause problems during storage, transportation, and use.

Process optimization is performed by using mathematical models in order to obtain the best quality value-added compost, and moreover, to manage the process more economically. Modeling is applied to predict the dependent variable as accurately as possible, especially when independent variable values are not available. Although some mathematical models allow values to be subjected to different statistical evaluations, these models have some limitations such as linear model and distribution assumptions. Therefore, these models can only linearly model the relationship between input and output. The prediction performance of linear modeling increases when the relationships between variables are linear. Otherwise, the prediction performance decrease and some variables should be transformed. Even with this conversion process, the results may not meet expectations (Cagcag Yolcu et al., 2021).

Alternatively, ML, a subset of AI, has emerged as an effective way to address key methodological challenges in modeling. ML can manage complex multivariate data, predict non-linear connections, and process missing data (Manley et al., 2022). The approaches of machine learning are classified as supervised learning (regression and classification), unsupervised learning (clustering), and reinforcement learning approaches. Supervised learning is the most widely used approach (Hernandez-Matheus et al., 2022; Zhong et al., 2022). ML gains experience using data, learns patterns, makes informed inferences from data as creating a mathematical model, and provides predictions for the future. ML with the ability to make adjustments without being specially programmed to accomplish the target task uses computer algorithms. ML has become a promising technology to overcome design challenges as a tool with powerful computational capabilities for processing and analyzing big data. Since engineering applications are processes by which large amounts of data can be obtained, many researchers have focused on ML to accelerate challenging design processes, make more informed decisions, and uncover hidden information (X. Wang et al., 2022).

In composting processes, ML approaches are used to accurately predict CO_2 output from the composting of feedstock (Li et al., 2022), optimize the processing parameters for improving compost quality (Aycan Dümenci et al., 2021; Ding et al., 2022; Yılmaz et al., 2022), predict of compost maturity (Wan et al., 2022; Xue et al., 2019), monitor moisture content in industrial-scale composting systems (Moncks et al., 2022), estimate the enzymatic activity of compost (Chakraborty et al., 2014), and classify the maturity of compost (Kujawa et al., 2020). These applied models are based on theoretical, analytical, and statistical methods (Andrade Cruz et al., 2022).

Modeling composting process parameters is very significant in generating solutions and decision-making processes. Especially in recent years, different ML algorithms have been used in the modeling and prediction of composting process parameters. This review focuses on the level of success achieved by ML algorithms and provides a background for future studies, as well as highlighting the use challenges and shortcomings in modeling composting processes that are not addressed in the literature. Moreover, the factors affecting the composting process and compost quality were examined in detail, and the application of ML to the process parameters and success levels were evaluated.

2. Process management

The basis of a composting process is biochemical reactions that convert raw feedstocks into compost. Biochemical reactions occur spontaneously in the process, but due to the physicochemical properties of the feedstocks, the reactions may not always be suitable for the composting process. Process control in composting is carried out by monitoring the main process factors and making necessary adjustments to these factors. The main factors affecting composting processes are temperature, pH, moisture content, electrical conductivity, carbon content, nitrogen content, and the ratio of carbon to nitrogen. There are different levels in the literature for the optimum factor values of the final compost. These values were summarized in Table 1.

The conventional one-factor-at-a-time approach to model and optimization is time-consuming, non-feasible, and unsuccessful in getting the true optimum condition due to the lack of interactions among the factors. Various ML algorithms are widely applied for accurate, valid, and consistent modeling of composting process factors. In these algorithms, factors and optimum values that show the quality and maturity of the final compost are taken into account. These factors are considered in detail below. These factors are evaluated in detail below.

2.1. Temperature

Temperature is an important and reliable factor used to determine the success of the composting process. The heat released during the composting process affects the biochemical activity due to microbial activities (Rynk and Ziegenbein, 2021). By the feedstock that acts as insulation, the rate of heat dissipation slows down and the temperature of the pile rises. The increase in temperature supports material stabilization and removal of volatile compounds and moisture. However, at lower temperatures (<40 °C), organic matter decomposes more slowly, nutrients are retained, and less odor and volatile compounds are released. The increase in temperature as a result of the decomposition of organic matter can be noticed within a few hours. The inconsistent changes in temperature level at any stage of the composting process

Table 1
The optimum values for final compost.

Parameter	Optimal value	References
pH	7.0–8.5	(Chan et al., 2016; Chen et al., 2018; Szanto et al., 2007; Wong et al., 2009)
pH	7.0–8.0	(Chung et al., 2021)
pH	5.5–7.0	(Vitinaqailevu and Rajashekhar Rao, 2019)
pH	6.5–7.2	(Aycan Dümenci et al., 2021; Singh et al., 2012; Yılmaz et al., 2022)
EC (mS/cm)	<4	(Chung et al., 2021; Dhanker et al., 2021; Kabak et al., 2022; Li et al., 2007; Liu et al., 2018; Yao et al., 2015; Zhang and Sun, 2016)
EC (mS/cm)	<3	(Ma et al., 2022; Soumaré et al., 2002)
TN (%)	<3	(Aycan Dümenci et al., 2021)
		(Aycan Dümenci et al., 2021; Barker, 1997)
TOC (%)	8–35	(Aycan Dümenci et al., 2021; Rynk, 1992; Yılmaz et al., 2022)
C/N	<25	(Chen et al., 2018; Wang et al., 2017)
C/N	<20	(Awasthi et al., 2016a; Bayındır et al., 2022; Bernal et al., 2009; Chung et al., 2021; Goyal et al., 2005; Li et al., 2021; Mathur et al., 1993; Shan et al., 2013)
C/N	<15	(Jiang et al., 2015; Zhao et al., 2020)
C/N	16–20	(Elango et al., 2009; Ma et al., 2022)
C/N	15–20	(Vitinaqailevu and Rajashekhar Rao, 2019)
C/N	<12	(Bernal et al., 1998)
C/N	10–15	(Gómez-Brandón et al., 2008)
NH_4^+-N/NO_3^--N	<0.5	(Akdeniz, 2019)
NH_4^+-N/NO_3^--N	<1.0	(Ko et al., 2008; Li et al., 2021)
NH_4^+-N/NO_3^--N	<3	(Yu et al., 2019; J. Zhang et al., 2016)

indicate that there is a problem in the process. Microbial activity, and therefore temperature can be reduced due to poor aeration, low moisture content, or a loss of nutrients. Conversely, heat accumulation can raise temperatures to levels that adversely affect microorganisms (Diaz et al., 2007). In either case, increasing aeration, agitating the heap, and adjusting the moisture content will make the composting process more efficient (Michel et al., 2021). Therefore, temperature changes in the compost pile should be regularly monitored, recorded, and evaluated.

Different countries have different rules and regulations for the sanitation of compost. However, the temperature/time relationship is an almost universal parameter. In order to achieve the desired effect in pathogen destruction, the required temperatures must be reached and stayed for enough time at these temperature values (Oshins and Michel, 2021; Xiao et al., 2017). USEPA indicates that the threshold temperature to destroy pathogens must achieve above 55 °C for three days in the aerated static pile or in-vessel composting process. However, in the windrow composting process, it must remain above 55 °C for fifteen days or longer, with a minimum of five rotations during that time (Bernal et al., 2009; Epstein, 1997; USEPA, 1985). While some of the weed seeds can be destroyed in a few hours at 55 °C, it is necessary to go above 60 °C to destroy most of them. Moreover, some species can even survive these high temperatures (Dahlquist et al., 2007).

2.2. Moisture content

Moisture content (MC) during the composting process is the most important factor affecting biological activity in the decomposition of feedstocks. Besides, one of the most important properties of feedstocks that affect the operation of the process is the initial moisture content. The moisture surrounding the feedstocks supports the movement and metabolic processes of microorganisms. Moisture allows both nutrients and oxygen to be dissolved and transported by diffusion (Godlewska et al., 2017). Therefore, the moisture content should be adequate at the beginning of the composting process and throughout the process. At the beginning of the composting process, the moisture content should be kept between 40 and 65 % (Manu et al., 2021; Oshins and Michel, 2021). Preferably, it is recommended to range 50–60 % for rapid decomposition. The moisture content shows to downward tendency as the composting process progresses (Diaz et al., 2007; Epstein, 1997; Oshins and Michel, 2021). The increase or decrease in moisture content affects the process and the quality of the final compost. Because insufficient moisture content (<35 %) slows down biological activity, and its excess prevents oxygen transfer (Rynk and Schwarz, 2022). Biological activity inhibits below the moisture content of 15 %, but studies have reported that the composting process slows down significantly when dropped below 40 %. When the low moisture content is reached, water or wet feedstocks should be added to the process (Diaz et al., 2007; Rynk and Ziegenbein, 2021). As the moisture content increases, the liquid film layer surrounding the solid particles thickens. The excess moisture also causes material compaction and a decrease in pore space. This prevents airflow in the pores (Cáceres et al., 2018). Since oxygen diffuses more slowly in water, the transition to the anaerobic activity begins with the thickening of the liquid film layer. When the high moisture content (>65 %) is reached, the pile should be dried by turning, or dry amendments are added (Zhou et al., 2022). It should be monitored whether a compost pile has the optimum level of moisture.

In the process, the decrease in moisture content can be caused by the insufficient initial moisture content of the raw material, excessive aeration, and ambient temperature. However, climatic conditions and types of feedstocks can result in high moisture content. The moisture content of a well-blended pile increases moving inward from the surface. Moisture content should be measured to determine whether a feedstock is suitable for composting, feedstock mixing ratios and the maturity of the compost. The moisture content of the final compost should be around 30 % at the end of the composting process (Diaz et al., 2007).

2.3. pH

pH is an important factor in composting process. The broad spectrum of microorganisms and natural buffering capacity in the composting process allows the process to proceed in a wide pH range. Therefore, it is not taken into account at the beginning of the process for effective composting. However, it can be useful to use additives at very low (<5.5) and very high (>9) pH values of the compost feedstock, although this is rarely encountered. Low pH values can inhibit microbial activity, while high pH values can encourage ammonia evaporation and reduce some compost quality. The pH range of 6.5–8.0 is preferred for feedstocks in composting process.

pH tends to change during the composting process. The pattern and extent of pH change depend on the compost feedstocks and process conditions. In the early stages of composting, the carbon compounds in the feedstocks cannot be completely oxidized to CO_2. Organic acids such as acetate, propionate, and butyrate are formed and the pH drops rapidly to levels between 4 and 5. The pH usually rises with the decomposition of organic acids and reaches near neutral values, when oxygen is available. However, when aeration is poor, organic acids can persist and pH cannot rise until the acids are broken down. Organic acids often decompose quickly and the pH drop takes a very short time depending on the feedstocks. After this step, the pH either remains constant or rises slightly due to the ammonium (NH_4^+) formation and its subsequent conversion. The NH_4^+ normally turns into gaseous ammonia (NH_3) over time. Ammonia evaporation increases greatly at high pH (above 7.5–8.0). NH_3 causes a serious odor problem in the composting process and reduces the nitrogen content of the final compost. In this case, ammonia loss can be limited by adding more acidic feedstocks or additives. In addition, at the beginning of the process, ammonia is converted into microbial protein and preserved by adjusting the C/N ratio to 30/1 with raw materials and additives.

2.4. Electrical conductivity

Electrical conductivity (EC) is a parameter that can directly reflect the salt content of the compost. Salt accumulation in the soil is one of the important factors affecting land degradation. It reduces agricultural production, especially in arid and semi-arid regions. Salinity inhibits plant growth due to the low osmotic potential of the soil solution, ion toxicity, and ion imbalance, which further reduces nutrient uptake. EC is an indicator of compost maturity. It is influenced by the temperature, total concentration and valance of ions. EC usually rises in the initial stage of composting process. It is considered that the increase may be related to the vigorous microbial activity that accelerated the degradation of organic materials into simple compounds and rapidly produced numerous micromolecular organic acids (Ma et al., 2022) and water-soluble mineral ions (phosphate, sulphate, ammonium, sodium, and potassium) (Jiang et al., 2014). Then, EC gradually decreases during the process. It can be explained by the leaching of salts, the decomposition of organic acids, and thus the maturation process (Wichuk and McCartney, 2010). If the EC of the compost is high, some additives can be used to reduce the EC due to the dilution effects and/or salt adsorption potentials.

2.5. Nitrogen

Nitrogen (N) is an essential nutrient in biochemical processes. Nitrogenous compounds continually change due mostly to the activities of microorganisms. A feedstock contains primarily organic nitrogen and smaller amounts of nitrate (NO_3^-) and ammonium (NH_4^+). The NO_3^- and NH_4 forms of N are evaluated as “available N” since they are soluble in water and directly usable by microorganisms and plants. Nitrogen transformation occurs in four ways called as ammonification, nitrification, denitrification, and biological immobilization (Cáceres et al., 2018; Lu et al., 2018; Shan et al., 2021; Wang et al., 2017). Nitrogen loss causes odor pollution, equipment corrosion, acid rain, and atmospheric nitrogen rise. It also reduces the agricultural quality of the final product. Large amounts of total nitrogen (TN) are lost through gaseous emissions caused by the transformation of nitrogen during composting (Liu et al., 2021). TN value of the compost, which is the final product, is required to be above 1 % in order to avoid the need for supplemental nitrogen fertilizer to improve the soil and thus plant growth. However, the TN value should not be > 3 %. In this case, compost is considered immature (Barker, 1997; Herity, 2003).

NH_4^+/NO_3^- ratio is one of the maturity indexes in compost. It is also known as the oxidation index or nitrification index of mineral forms of nitrogen. Therefore, the lower the NH_4^+/NO_3^- value, the higher the maturity (Bernal et al., 2017). The value of NH_4^+/NO_3^- ratio below 3 shows mature compost (Zhang et al., 2016).

2.6. Carbon

The organic carbon contents of the feedstocks during the composting process reflect the degree of humification of feedstocks. In feedstocks, organic carbon components include hemicellulose, cellulose, lignin, and in addition organic matter in a water-soluble form such as starch, oligosaccharides, sucrose, fructose and amino acids (Said-Pullicino et al., 2007).

In the composting process, feedstocks and energy sources for microorganisms are water-soluble organic substances. The solubility of organic substances in water depends on the degree of conversion of the organic matter and the stability of the materials (Loow et al., 2017; Ravindran et al., 2022; Yu et al., 2019). Carbon is the backbone of the molecules that create organic matter (Stehouwer et al., 2021). Carbon is necessary for the structure of the cell of microorganisms and for the synthesis of various organic molecules. Moreover, it constitutes about 50 % of the dry mass of microorganisms. During the composting process, the carbon content and the rate of CO_2 formation decrease as metabolic activity decreases (Epstein, 1997). The decomposition gases that include carbon, are carbon dioxide (CO_2), methane (CH_4), and carbon monoxide (CO). The loss of carbon during composting is due to the gases formed and the mineralization of organic matter (Cui et al., 2016; Said-Pullicino et al., 2007).

2.7. Carbon to nitrogen ratio

Carbon (C) and nitrogen (N) contents of feedstocks are affected composting process and the quality of the final compost. Microorganisms, which are the main actors of the composting process, need nitrogen for protein production and cellular reproduction, and carbon for energy needs and growth (Wang et al., 2022). In general, microorganisms have 10 to 15 units of carbon per unit of nitrogen by weight. However, the microorganisms constantly lose carbon through respiration. Microorganisms must consume about 25 folds more carbon resources than nitrogen to recover the carbon lost as CO_2. Therefore, it is important to keep the carbon and nitrogen at suitable rates when selecting and mixing the feedstocks to be composted at the beginning of the composting process. At the beginning of the process, it is reported that successful composting can be done with a C/N ratio of 20/1 to 60/1. However, for individual feedstocks or their mixtures, the C/N ratio between 25/1–40/1 is agreed with ideal (Rynk and Schwarz, 2022). A C/N ratio below 20/1 means that microorganisms quickly consume carbon and is not converted all nitrogen into cellular compounds that occur the volatile nitrogen compounds such as ammonia and nitrous oxide (Cerda et al., 2018). In this case, almost half of the total nitrogen content at the start of the process is lost, and ammonia can inhibit microbial activity (Wang and Zeng, 2018). Cellular reproduction is slowed down with a C/N ratio above 40/1 due to nitrogen deficiency. This causes enough microorganisms to build up to break down the carbon and slow the composting process. However, a high initial C/N ratio reduces composting efficiency, and complicates process management. Nitrogen in almost all feedstocks is completely biodegradable, while lignin-containing carbon compounds have low biodegradability (Sanchez-Monedero et al., 2018). Applications such as additives, bulking agents, and microbial additions can be made to adjust the C/N ratio of feedstocks. Thus, the process efficiency and quality of compost are improved (Manu et al., 2021; Zhou et al., 2022).

C/N ratio reduces as the organic carbon is mineralized during the composting process. C/N ratio of the compost should be < 20/1 (preferably < 18/1) for agricultural and horticultural usage as it can cause nitrogen immobility. The compost with a higher C/N ratio can be used for mulch and erosion control (O'Neill and Rynk, 2021; Rynk and Schwarz, 2022; Wang and Zeng, 2018).

3. Prospects from ML and AI in the composting process

Although the composting process is an effective method of integrated solid waste management that provides waste disposal and recycling, it is important to analyze, predict, and optimize the factors affecting the process in an accurate, valid, and consistent manner in solution and decision-making processes. The analysis of composting process factors has been carried out by scientists using various ML algorithms as well as traditional statistical-based models, especially in recent years. Moreover, few researchers have used AI techniques to optimize composting parameters. Although all these techniques and modeling tools have produced impressive results, there are also some inadequacies when examined from a holistic perspective. These inadequacies include data acquisition, time and resources, interpretation of results, and high error susceptibility (Chhaya et al., 2020). ML requires data sets at enough numbers to train on, and these should be inclusive/unbiased, and of good quality. ML needs substantial time to let the algorithms learn to get satisfactory accuracy. Moreover, most of the time, it can be required additional computing power. The correct interpretation of the results produced by the algorithms based on the correct metric is especially important in performance evaluation.

4. Machine learning models

ML, which is constantly evolving, can be seen as the most basic subfield of AI. Scientists focus on ML because it produces high-value predictions that can guide better decisions and smarter actions without human intervention. The main tasks of ML methods are classification and regression. In terms of ML, classification is the task of using algorithms that learn by assigning a class label to samples. The regression problem, which arises when the output variable is a real or continuous value, is a task that tries to best create the data in the hyperplane passing through the points in a learning process. A presentation of a machine learning flowchart was given in Fig. 1.

ML algorithms, such as artificial neural network (ANN), adaptive neuro-fuzzy interference system (ANFIS), *k*-nearest neighbors (KNN), random forest (RF), and support vector machine (SVM), have been used to predict or classify composting factors. Schematic presentations of ML algorithms and flowcharts applied for modeling of the composting process were presented in Figs. 2 and 3. Moreover, in a limited number of studies in the literature, *meta*-heuristic optimization algorithms such as genetic algorithms, particle swarm optimization, and differential evaluation algorithm have been applied to determine the optimal inputs that will produce the desired values of the model parameters. A summary of ML applications in composting processes was given in Table 2.

The achievements to be obtained by using ML methods as prediction and/or classification and optimization tools in the composting process are (*i*) high fit to datasets containing structurally non-linear relationships produces superior prediction and/or classification performances, (*ii*) factor values to be produced by possible inputs are predicted without the need for a new experimental design with a function representing the relationship between inputs and outputs in the composting process, (*iii*) optimization of composting factors through ML models trained as

Fig. 1. A presentation of a machine learning flowchart.

predicted functions of relationships provides information about desired input values.

4.1. Artificial neural networks

Artificial neural networks, as a basic area of AI, aim to produce solutions to common problems by simulating the human brain. ANNs, just like a human, have the skills such as deriving and discovering new information through learning (Bayındır et al., 2022). Feed-Forward Neural Network (FFNN), which is a kind of Multilayer Perceptron (MLP) proposed by Werbos, and re-considered by Rumelhart et al. (Rumelhart et al., 1986; Werbos, 1974), was mostly used to predict the parameters in composting process (Alavi et al., 2019; Aycan Dümenci et al., 2021; Dragoi et al., 2021; Gebreyohannes et al., 2016; Guo et al., 2022; Moncks et al., 2022; Najafi and Faizollahzadeh Ardabili, 2018; Shi et al., 2022; Sidełko et al., 2019; Wu et al., 2013). The schematic

Table 2
Summary of machine learning (ML) applications in composting processes.

Feedstock	Inputs	Problem	Prediction	ML models	Performance	Structure	Advantages	Disadvantages	Ref.
Spent mushroom & wheat straw	C/N Temperature Time	R/P	The volume of produced biogas (VB)	MLP ANFIS Logistic Model	at the mesophilic temperature RMSE = 0.1940 (ANFIS), 0.7800 (MLP), 0.5111 (LM) R = 0.9998 (ANFIS), 0.9981 (MLP), 0.9992 (LM) at the thermophilic temperature RMSE = 0.3033 (ANFIS), 0.3430 (MLP), 0.5506 (LM) R = 0.9997 (ANFIS), 0.9992 (MLP) 0.9991 (LM)	Non-Linear/ Crsip - Fuzzy	Assumption-free data based Non-Linear Model	No external comparison For internal comparison can be used MAPE No optimization Trail Error Method for Hyperparameter Tunning	(Najafi and Faizollahzadeh Ardabili, 2018)
Oily sludge	Composting type Time Petroleum content	R/P	Hydrocarbon Organic carbon degradation	ANN DEA	AARE = 5.96 % for TPH AARE = 12.70 % for OC	Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	No external comparison No optimization	(Dragoi et al., 2021)
Organic fraction of MSW	Aeration variant Hydraulic load Thickening coefficient Airflow direction Time	R/P	Pressure drop	MLP RBF	R = 0.9620 (MLP/5–9–1)	Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	No external comparison No optimization	(Sidełko et al., 2019)
Chicken manure & penicillin	Penisilin G pH C/N	C	Humus Fulvic acid Humic acid	RF LR	–	Linear/ Crisp Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	Just Linear or Just Nonlinear No external comparison No optimization	(Kang et al., 2022)
Ganoderma lucidum residue & fresh cow dung	C/N MC Bacterial agent type Time	R/P — O	Humic Acid	MLP GA	RMSE = 2.2112 R^2 = 0.7952	Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	No external comparison For internal comparison can be used MAPE Trail Error Method for Hyperparameter Tunning	(Shi et al., 2022)
Chicken manure & bagasse	Time Antibiotic type % w bagasse Co	R/P	TCs removal efficiency	MLP	R=0.9914	Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	No external comparison For internal comparison can be used MAPE No optimization Trail Error Method for Hyperparameter Tuning	(Alavi et al., 2019)
Cattle manure & municipal solid waste	Time Cattle manure ratio	R/P - O_{MO}	Temperature pH EC MC TN C/N TOC	CFNN	MAPE/ RMSE=4.29%/ 1.3189 - T MAPE/ RMSE=2.12%/ 0.1647 - pH MAPE/ RMSE=5.02%/ 0.0297 - EC MAPE/ RMSE=2.90%/ 0.9461 - MC	Linear & Nonlinear/ Crisp	Assumption-free data based Linear & Non-Linear	Trail Error Method for Hyperparameter Tuning	(Bayındır et al., 2022)

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Table 2 (*continued*)

Feedstock	Inputs	Problem	Prediction	ML models	Performance	Structure	Advantages	Disadvantages	Ref.
					MAPE/ RMSE=3.45%/ 0.0177 – C/N MAPE/ RMSE=3.61%/ 0.5592 - TOC				
Olive mill waste & natural minerals	Time Olive-mill waste ratio	R/P - O_{MO}	Temperature pH EC MC TN C/N	MLP-FFNN MLP-ERNN	MAPE<2% -T MAPE <5‰ -pH MAPE <1 - EC MAPE <1% - MC MAPE <1% - TN MAPE <1% - C/N	Non-Linear/ Crisp	Assumption-free data based Linear & Non-Linear	Trail Error Method for Hyperparameter Tuning	(Aycan Dümenci et al., 2021)
Tea waste & food waste	TW ratio Time	R/P — O	Temperature pH EC C/N MC loss TN loss TOC loss	RBF GA	R^2=99.9795% - T R^2=99.9406% - pH R^2=99.9736% - EC R^2=98.9486% - C/N R^2=99.9492% - MC loss R^2=99.6935% - TN loss R^2=99.9764% - TOC loss	Non-Linear/ Crisp	Assumption-free data based Non-Linear Model Reliability/ Validity İnvestigation Optimization	Trail Error Method for Hyperparameter Tuning	(Yılmaz et al., 2022)
Swewega sludge & agro-industrial wastes	Time Temperature Moisture from a capacitive sensor Air temperature Humidity Moisture from Gravimetry	R/P	MSTR Drying	IBK based on KNN MLP LR	R^2=98.79% - IBK-KNN R^2=96.18% - MLP R^2=98.79% - LR	Linear/ Crisp Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	Trail Error Method for Hyperparameter Tuning for some used ML models No external comparison No optimization	(Moncks et al., 2022)
Kitchen waste	Time Temperature pH EC MC TN C/N Ammonia nitrogen Organic matter Nitrate TOC Seen germination index	R/P	Composting maturity	LR KNN DT SVR Stacking	R^2/RMSE/MAE LR: 0.73/9.41/ 7.06 KNN: 0.87/6.57/ 4.33 DT: 0.76/8.89/ 5.16 SVR: 0.69/ 10.21/7.09 RF: 0.85/7.09/ 3.94 STC: 0.88/6.46/ 3.79	Linear/ Crisp Non-Linear/ Crisp	Assumption-free data based Contains Ensemble Model	No optimization Just Linear or Just Nonlinear Trail Error Method for Hyperparameter Tuning	(Ding et al., 2022)
Green waste & meat waste	MC Org. C TC TN TP AP LOI Sand Silt PAH Time	R/P	PAHs	MLP RBF SVRM5 Model Trees (M5P) M5 Model Rules (M5R) LR	RMSE=0.153 - MLP RMSE=0.225 - RBF RMSE=0.262 - SVR RMSE=0.355 - M5P RMSE=0.347 - M5R RMSE=0.344 - LR	Linear/ Crisp Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	Just Linear or Just Nonlinear No optimization Trail Error Method for Hyperparameter Tuning	(Wu et al., 2013)
Pig manure	Temperature (inside the bioreactor) SM O_2 Volume CO_2 Time	R/P	Total heat losses	RF KNN DT AdaBoost Bagging Gradient Boost	R=0.9871	Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	Trail Error Method for Hyperparameter Tuning for ANN No external comparison No optimization Trail Error Method	(Boniecki et al., 2013)

(*continued on next page*)

Table 2 (*continued*)

Feedstock	Inputs	Problem	Prediction	ML models	Performance	Structure	Advantages	Disadvantages	Ref.
	Organic substance mass Ambient temperature Dry substance mass							for Hyperparameter Tuning	
Green waste	TOC TN C/N Cellulose Hemicellulose Lignin	C - R/P	CO_2	RF KNN DT AdaBoost Bagging Gradient Boost	RMSE= 23.3 - RF RMSE=24.5 - KNN RMSE=30.2 - DT RMSE=25.5 - AB RMSE=26.1 - B RMSE=27.1 - GB	Linear/ Crisp Non-Linear/ Crisp	Assumption-free data based Linear Model	No external comparison No optimization	(Li et al., 2022)
Swine manure	TOC TN C/N Cellulose Hemicellulose Lignin	C - R/P	CO_2	MLP SVR DT Gradient Boosting	MSE/R^2=365/ 0.56-GBR MSE/R^2=69/ 0.55-GBR MSE/R^2=60/ 0.79-GBR MSE/R^2=446/ 0.29-DTR MSE/R^2=60/ 0.81-GBR	Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	No external comparison No optimization	(Guo et al., 2022)
Dairy yard waste, dairy manure, chopped plant litter, kitchen waste	No understood	R/P	Fluorescein diacetate hydrolysis (FDA-HR)	PLS PCR RF SVR PSR MLP	RMSE=13.38 - MLP R^2=0.92 - MLP	Linear/ Crisp Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	Trail Error Method for Hyperparameter Tuning for some used ML models No external comparison No optimization	(Chakraborty et al., 2014)
Sewage sludge & rapeseed straw	Images of compost samples	C	The stage of early maturity (ycomp1) not reach this stage (ycomp0)	CNN	CE=0.51% -CNN16MIX	Non-Linear/ Crisp	Assumption-free data based Non-Linear Model	Trail Error Method for Hyperparameter Tuning No external comparison No optimization	(Kujawa et al., 2020)
Poultry waste & food waste	Mixture ratio Time MC EC Temperature pH C/N	R/P — O	Nitrogen loss	RSM CFNN	RMSE=2.3364-HCFNN MAPE=6.56%-HCFNN	Linear & Non-Linear -Hybrid/ Crisp	Assumption-free data based Linear & Non-Linear Hybrid Parameter Optimization	Trail Error Method for Hyperparameter Tuning	(Kabak et al., 2022)

Problem Types – Regression: R; Prediction: P; Classification: C; Optimization: O; Multiobjective Optimization: O_{MO}.

architecture and working principle of ANNs were shown in Fig. 2(a) and 3(a), respectively. Different ANN types have produced successful results in non-linear modeling problems with their superior adaptability to the data structure. Apart from FFNNs, Elman Recurrent Neural Network (ERNN) (Aycan Dümenci et al., 2021), Radial Basis Function (RBF) Neural Networks (Sidełko et al., 2019; Wu et al., 2013; Yılmaz et al., 2022), Cascade Forward Neural Networks (CFNNs) (Bayındır et al., 2022; Kabak et al., 2022), and Convolutional Neural Networks (CNNs) (Kujawa et al., 2020) were also used in composting process prediction/ classification problems. Although successful results were obtained in process prediction/classification problems by using different types of ANNs for composting processes, the difficulties and problems encountered during the use of ANNs were ignored. The main disadvantages and difficulties of ANNs, which are not addressed in the studies reviewed and can be seen as a holistic deficiency of the relevant literature, are summarized as follows.

Black Box Nature; Probably the most well-known disadvantage of ANNs is their limited ability to clearly identify possible causal relationships and called "black box" structures (Tu, 1996). While it is not possible to interpret how and why ANNs produce a certain output, it is possible to interpret the output in detail with algorithms such as decision trees with a comparative perspective. For many problems, it is critical that models be interpretable.

Data-dependency; As an ML model, ANNs generate products based on data fed to them. Thus, ANNs are known as data-driven models. This feature, data dependency, is another disadvantage of ANNs. Similar to other ML algorithms, too small to not be inclusive or biased training sets will lead ANNs to produce biased and erroneous results. However, a simple algorithm like Naive Bayes is the appropriate choice in case of very little data.

Time Complexity-Time-Consuming; The computational complexity of ANNs or computational cost depends extremely on the size of the data, and also on the complexity of network architecture. For the same task, an ANN with just one hidden layer will be much faster than a random forest with one thousand trees, while one with fifty hidden layers will be much slower than a random forest with only ten trees.

Pre-processing of Data Requiring Attention; Data preprocessing is also a vital issue for ANNs, as with many other ML algorithms, since ANNs are pretty sensitive to input data. Generally, this transaction is carried out by scaling the data and if this is not fulfilled properly, it can lead to a

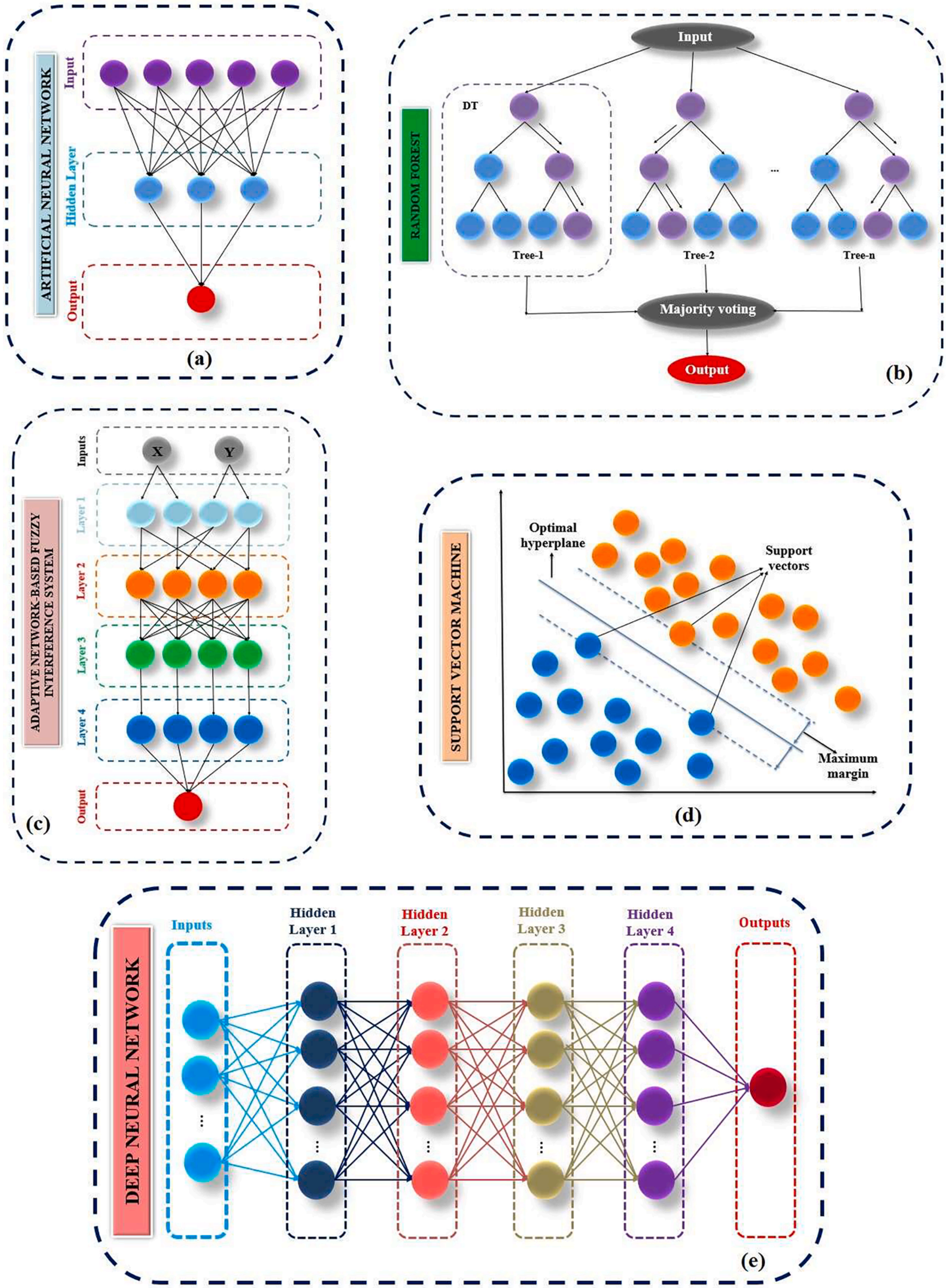

Fig. 2. Schematic presentation of artificial neural networks (a), random forest (b), adaptive network-based fuzzy inference system (c), support vector machine (d), and deep neural network (e).

suboptimal model.

Sidełko et al. (2019) used MLP to develop a model that could be used to determine the resistance of airflow through a bed in composting process. The training of the MLP was carried out with the Quasi-Newton (BFGS) algorithm and hyperparameters such as the number of hidden layer neurons and activation functions were determined by trial-and-error method. The study was focused on modeling non-linear relationships by MLP. R was obtained as 0.962 for the best model (Sidełko et al., 2019).

Shi et al. (2022) investigated the attenuation of tetracyclines during chicken manure and bagasse composting and used MLP to predict the TCs removal efficiency. The hyperparameters of the network, such as #

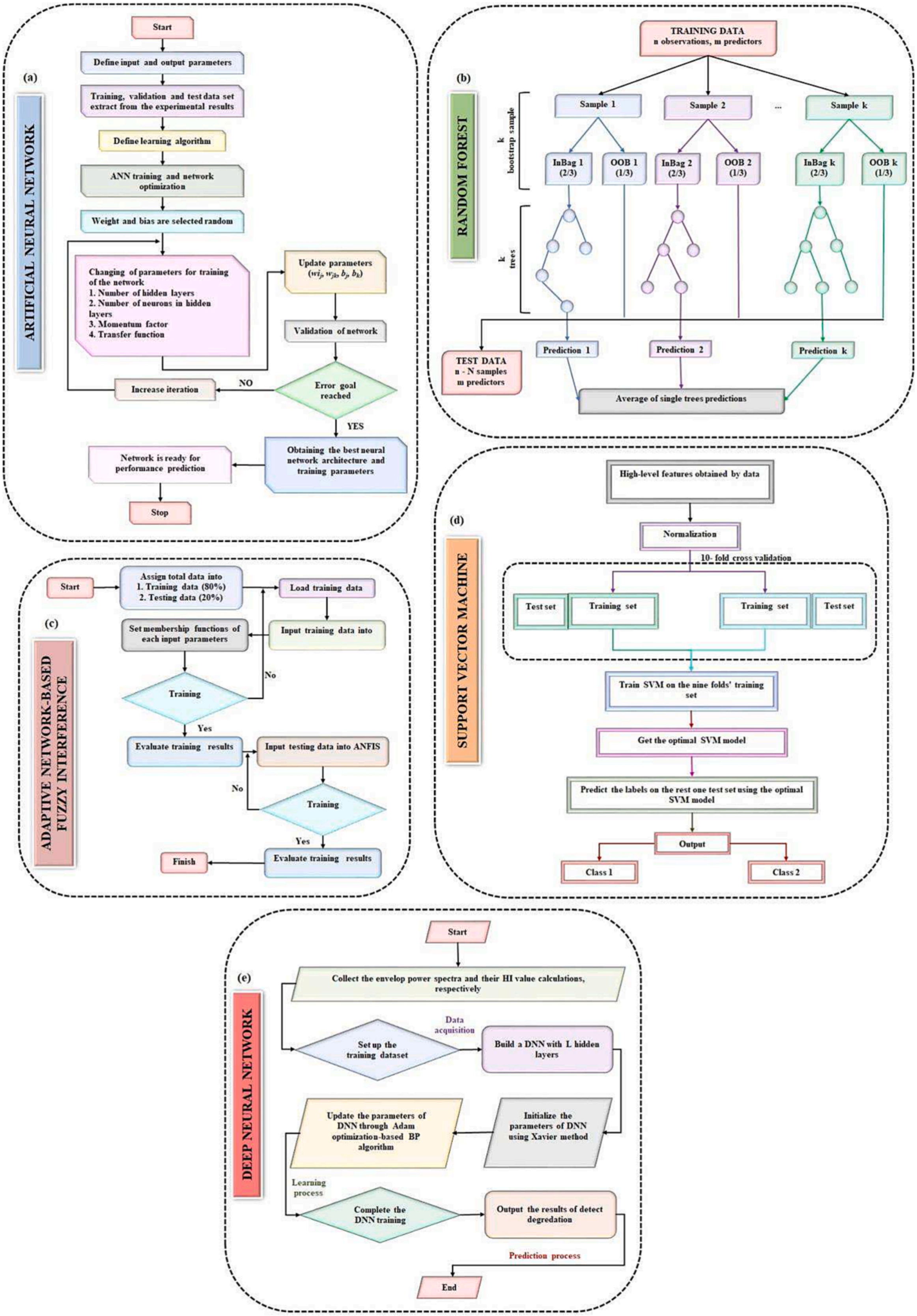

Fig. 3. Schematic flowcharts of artificial neural network (a), random forest (b), adaptive-network-based fuzzy inference systems (c), support vector machine (d), and deep neural network (e).

of hidden layers and # of hidden layer neurons were determined by trial-and-error method. MSE was used as the loss function in MLP training. A measure of the linear relationship between observed and predicted values was obtained as $R = 0.991$ (Shi et al., 2022).

Dragoi et al. (2021) proposed a neuro-evolutive methodology to predict total petroleum hydrocarbons (TPH) and organic carbon (OC). The model was based on ANNs and differential evolution (DE). ANN models had the ability to model non-linear relationships by their nature. DE was used to train the ANN and to determine the model parameters such as # of hidden layer neurons, and activation function. In the optimization process, Mean Square Error (MSE) and Average Absolute Relative Error (AARE) were used the evaluation of the performances (Dragoi et al., 2021).

Dumenci et al. (2021) put forward a study for identifying the maturity of the co-compost of olive mill waste and natural mineral materials and used MLP neural networks (FFNN and ERNN). By using two activation functions such as linear and sigmoid activation functions in the output layer neuron, totally-four different neural networks were created to predict the parameter of the co-composting process. The prediction results were compared by using RMSE and MAPE metrics with Response Surface Methodology (RSM). The low relative errors of NNs pointed to a great improvement over RSM results. Optimization were successfully achieved by GA (Aycan Dümenci et al., 2021).

Alavi et al. (2019) focused on the composting of chicken manure with penicillin-G. Backpropagation Artificial Neural Network (BPNN) was used to predict humic acid in the composting process of *Ganoderma lucidum* residue. Also, GA was used over the trained BPNN to optimize composting parameters such as the C/N ratio, initial MC, inoculant type, and composting duration. The hyperparameters of the BPNN, such as # of hidden layers and # of hidden layer neurons were determined by trial-and-error method. The activation function was Rectified Lineer Unit (ReLU). BPNN had an ability just model non-linear relationships. The results were evaluated by RMSE, R^2 and MSE metrics. The optimum parameter values in the composting process were determined by GA (Alavi et al., 2019).

Moncks et al. (2022) investigated ML models, such as LR, MLP, and IBK based on KNN to predict moisture content in industrial-scale composting systems. Performance evaluation was made by using R, and R^2, RMSE, MAPE, Root Relative Squared Error (RRSE), Mean Absolute Error (MAE) metrics. Instead of comparing the findings with different methods, the results were limited to the three methods. Consequently, the most successful model was IBK, while the most unsuccessful results were produced by LR (Moncks et al., 2022).

Guo et al. (2022) focused on predicting and optimizing heavy metal immobilization in composting process by using MLP, SVR, Decision Tree Regression (DTR), Gradient Boosting Regression (GBR), and GA. The predictions were compared by MSE and R^2, and GBR performed best (Guo et al., 2022).

Yılmaz et al. (2021) suggested using RBF to model the process parameters in the co-composting of tea waste and food waste and using GA to optimize the predictions. The prediction results produced by the RBF, together with the FFNN (non-linear model), SVR (linear and non-linear model with different kernels), and RSM (linear model) results, were evaluated from different perspectives. A comparative evaluation was made using RMSE and MAPE error metrics. The individual performance and the power of the model fit of RBF were examined with the characteristics of simple linear regression, and the R^2 coefficient. RBF produced both small (validity) and close (reliability) results. Desirability levels were above 95 % for all experimental designs except one (Yılmaz et al., 2022).

Bayındır et al. (2022) focused on modeling process parameters in the co-composting of cattle manure and municipal solid waste using a CFNN capable of modeling both linear and non-linear relationships. The prediction results were evaluated by RMSE and MAPE metrics. The results from CFNN were compared RSM (linear model) and computational-based MLP (non-linear) model. CFNN outperformed both linear and non-linear models with relative errors of < 5 % for all parameters. Moreover, the mixture ratio and time were optimized by multi-objective optimization (Bayındır et al., 2022).

Kabak et al. (2022) used a hybrid cascade prediction model based on CFNN and RSM to predict and model nitrogen losses in the co-composting process. The proposed hybrid model allowed simultaneous modeling of both linear and non-linear relationships with the structure of CFNN. RMSE and MAPE metrics were used to evaluate the prediction results. The results were compared RSM and MLP models. Moreover, optimal values of the parameters were determined by GA. (Kabak et al., 2022).

4.2. Decision tree and random forest

A tree structure can be associated with a wide area of ML, covering both classification and regression. Therefore, in decision analysis, a decision tree can be used to visually and explicitly represent decisions and decision-making, inspired by a tree. As the name suggests, Decision Tree (DT) uses a tree-like decision model. A decision tree is created upside down with its root at the top. DT is a flowchart-like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label. DT based on binary partitioning structure. The basic idea of DT is to recursively divide the dataset into smaller subsets to minimize variability within the subsets. DT creates a tree structure to ultimately perform the classification and regression function with these operations (Kannangara et al., 2018). DT generally tends to create large complex trees that will cause over fitting problems (Heshmati et al., 2014). RF can be considered an ensemble model based on DT, which can effectively reduce the risk of over fitting. RF consists of a series of decision trees and converts the averages of their predictions into final predictions based on the bagging and random feature selection strategy (Yu et al., 2020). The illustrations of RF architecture and working principle were presented in Fig. 2(b) and 3(b), respectively.

Although DT and RF, which are ML algorithms, are widely used for parameters prediction and/or classification in the composting process, the challenges and disadvantages of the algorithms have not been discussed. The disadvantages that can cause misconceptions during the use of DT and RF are data-dependency, overfitting, time complexity-time consuming, partitioning in continuous data, and tending to attributes with multi-valued (Jing-ti and Yu-jia, 2009; Patel and Rana, 2014; Thakur et al., 2010). As an ML model, DT is a data-driven model, and any minor changes to the data can lead to drastic changes in the DT's overall appearance and results. In the case of the small training data set in can be encountered may be overfitted or over-classified results, especially in Iterative Dichotomiser 3- ID3 algorithm. To make a decision, only one feature is tested at an instance, which takes a lot of time (ID3, C4.5, and Classification and Regression Tree-CART algorithms). Partitioning is a crucial challenge in DT. Features with discrete values can be easily partitioned however the variables with continuous values cause critical problems in partitioning while decision tree construction. DT generally selects the attribute with many values (ID3 and C4.5 algorithms). Thus, the algorithm can generate the wrong classification/regression structure. Moreover, sometimes the gain ratio of some non-valuable can be higher than those of some valuable features.

DT and RF have been used for the prediction of composting process parameters with various ML methods in different studies (Boniecki et al., 2013; Chakraborty et al., 2014; Guo et al., 2022; Wu et al., 2013). Ding et al. (2022) used the single and ensemble ML approaches to predict kitchen waste composting maturity, and applied different ML methods such as LR model, KNN, DT, and SVR and Stacking model. In the evaluation of the results generated by ML models, RMSE, MAE, and R^2 metrics were used. In terms of all metrics, ensemble models produced better predictions compared to single ML models. In addition, the Stacking model also had a superior performance with R^2, RMSE, and MAE on the training and test sets (Ding et al., 2022).

Lie et al. (2022) investigated the relationship between the experimental factors and CO_2 output to determine critical factors and focused to predict CO_2 production from GWC by utilizing ML methods. AdaBoost, Bagging, Gradient Boost, Random Forest KNN, and Decision Tree were chosen to compare the results. The performance criteria were RMSE and Gini index. The effect of outlier on the analysis was investigated. RF algorithm achieved the highest prediction accuracy when the outliers were eliminated. (Li et al., 2022).

Kang et al. (2022) focused on composting of chicken manure with penicillin G. The contribution rates of environmental factors to humification formation were determined by Variance Partitioning Analysis (VPA). The linear relations between humification and differential microbial genera were carried out by linear regression analysis. Bacterial communities and humification relationships were analysed by correlation analysis. While the linear relationships of HA and 5 pathways were significant a 1 % significance level, the relationships of 6 pathways were significant a 5 % significance level (Kang et al., 2022).

4.3. Adaptive-network-based fuzzy inference system

ANFIS which is a fuzzy inference system implemented in the framework of adaptive networks (Jang, 1993). ANFIS produces successful results in regression and classification problems of many fields by integrating principles and outstanding features of both neural networks and fuzzy logic in a single framework. The structure of ANFIS consists of five layers (Fig. 2(c)). The first layer is the one where the input parameters are fed to the fuzzy inference system. The second layer, which is also known as the rule layer, uses the membership values of the previous layer to evaluate the firing strengths of the applied rules. The next layer is the normalization layer and the evaluation of the normalized firing strengths for all the applied rules is carried out in this layer. In the fourth layer, defuzzification is performed using the normalized firing strength. Finally, the overall output of ANFIS is evaluated in step five by processing the node outputs of the previous step (Shafiullah et al., 2022). The operation of ANFIS, in a basic way was given with the flow chart in Fig. 3(c). ANFIS has basic limitations such as complexity due to dimensionality, lack of interpretability of the rules, and a large number of hyperparameters and their determination (Salleh et al., 2017).

In the literature, ANFIS has been used in a limited number of studies in modeling the parameters of the composting process. Najafi and Ardabili (2018) used MLP, ANFIS, and Logistic Model to predict the biogas production from spent mushroom compost (SMC). In this study, the hyperparameters of the ML models were determined by trial-and-error method, by considering the performance over the training set. Triangular-shaped, generalized bell-shaped, trapezoidal-shaped, and Gaussian membership functions were tested in ANFIS, and Gaussian was the best. The correlation coefficient (R), RMSE, and R^2 metrics were used as a measure of performance. R and R^2 metrics were obtained at 99 % and above in all models (Najafi and Faizollahzadeh Ardabili, 2018).

4.4. Support vector machines

Support vector machine is actually a ML method, which was first introduced by Cortes and Vapnik with the name support vector networks and originally created for two-group classification problems (Cortes and Vapnik, 1995). The working principle of SVR is based on finding a hyperplane in N-dimensional space that distinctly classifies data points. Hyperplanes, the number of which depends on the number of features, are decision boundaries that help classify data points. SVM uses the kernel method to achieve optimal data separation and commonly used kernel functions include linear, polynomial, radial basis function, and sigmoid (Sakr et al., 2016). The illustrations of SVM architecture and working principle were given in Fig. 2(d) and 3(d), respectively. SVM is used to solve regression problems, it is called SVR (Dai et al., 2011). In the literature, SVR has been used in a few studies in modeling the parameters of the composting process (Chakraborty et al., 2014; Wu et al., 2013).

SVM has some drawbacks and challenges like other ML algorithms (Fedorovici and Dragan, 2011; Karamizadeh et al., 2014; Yu et al., 2004). These are data dependency, extensive memory requirement - time complexity, choosing an appropriate kernel function, and pre-processing of data requiring attention. As an ML model, SVM is a data-driven model, and any changes to the data can lead to dramatic changes in the results of SVM. SVMs algorithmic and time complexity and hence memory requirements are very high. This is because all support vectors must be stored in memory, and this number increases abruptly with training dataset size. It is a crucial challenge to determine the appropriate kernel solution function. Using a high-dimensional Kernel function generates a lot of support vectors, which greatly increases the time complexity. Data preprocessing is essential for SVM as it is for many other ML algorithms since SVM is highly susceptible to input data. Preprocessing is often made by scaling data. An inappropriate scaling transaction can lead to misleading results.

Wu et al. (2013) used six ML models, MLP, RBF, Support Vector Regression (SVR), M5 Model Trees (M5P), M5 Model Rules (M5R), and LR, to predict 16 polycyclic aromatic hydrocarbons (PAHs) bioavailability in compost-amended soils. The performance of the ML models was evaluated in terms of Root Mean Square Error (RMSE) error metric. When the models were compared according to RMSE, the success order on the training sets was RBF > M5P > SVR > MLP > M5R > LR. According to the results, SVR showed the third-best performance (Wu et al., 2013).

Chakraborty et al. (2014) used Partial Least Squares (PLS), Principal Component Regression (PCR), Penalized Spline Regression (PSR), RF, SVR, and MLP to predict compost enzymatic activity. RMSE and coefficient of determination (R2) were utilized as performance metrics. For some ML models, hyperparameters were taken as the default of the software used, while others, such as MLP, were taken by the trial-and-error method. As a result, the most successful model was IBK, while the most unsuccessful was LR. The SVR produced results ahead of or equal to other non-MLP models (Chakraborty et al., 2014).

Although some different ML algorithms such as KNN, logistic regression, and linear regression are applied in the modeling of composting process, in the examined studies, these methods were not alone but were used together with other ML methods.

4.5. Deep neural networks

Deep Learning (DL), which is part of the ML family and is basically based on ANNs, is also used in composting process modeling in very few studies. The concept of “deep” in DL refers to the use of multiple layers in the network. DL neural networks differ from traditional NNs with their hidden layer numbers (i.e. their depth). DL can perform complex tasks that often require extensive feature engineering. One of the biggest draws of DL is its ability to work with unstructured data. The multiple layers in DNNs allow models to become more efficient at learning complex features (i.e., executing many complex operations simultaneously). DNNs such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) have been widely and successfully used in prediction and/or classification (Kirisci and Cagcag Yolcu, 2022). DNNs were used in only one study in the composting process. The illustrations of DNNs’ architecture and working principle were given in Fig. 2(e) and 3(e), respectively.

Kujawa et al. (2020) focused on the classification of the maturity of compost based on sewage sludge and rapeseed straw by using CNN. Classification error (CE, %) was used as the performance metric. Moreover, the classification performance of the best CNN architecture was also evaluated in terms of some measures such as correctly classified cases, misclassified cases, true positives, true negatives, false positives, and false negatives. Some hyperparameters were taken by trial-and-error method, while others were taken subjectively. The results of different CNN architectures recommended for use in the study were evaluated internally (Kujawa et al., 2020).

5. Artificial intelligence

AI referred to the simulation of human intelligence in machines can be identified as programmed machines that tend to behave like humans. The ideal characteristic of AI, just like for humans, is its ability to rationalize and take actions that have the best chance of achieving a specific goal. Many AI techniques such as genetic algorithms, particle swarm optimization, and differential evaluation algorithm are used in integration with ML algorithms. Schematic presentations of AI algorithms were presented in Fig. 4.

5.1. Genetic algorithm

GA is one of the most widely used AI techniques for optimization of composting process. A schematic presentation of GA was shown in Fig. 4 (a). GA is a metaheuristic algorithm designed for optimization purposes, based on the concept of survival of the fittest and biologically inspired by the natural selection process (Murray-Smith, 2012; Yalçınkaya et al., 2021). The algorithm begins to search with a randomly generated population. Each individual (chromosome) in the population represents potential solutions. GA conducts an optimization process consisting of a process that includes iterative operations. When an adequate solution is reached, GA stops the process. Each individual consists of potential values of parameters to be optimized, known as genes. GA is based on some basic concepts and parameters as (*i*) a collection of potential solutions (population), (*ii*) a function that represents a measure of how good the solution (fitness function), (*iii*) a mechanism for determining the most suitable individuals to be passed on to future generations (selection mechanism), (*iv*) # of individuals in a population (population size), (*v*) a genetic operator that is used to alter individuals from one generation to the next and is performed based on the crossover probability (crossover operator), (*vi*) a genetic operator that is used to maintain the genetic diversity of a population and is performed based on the mutation probability (mutation operator), (*vii*) a selection system that individuals with poor fitness value to be not transferred to new generations and is performed based on the natural selection ratio (natural

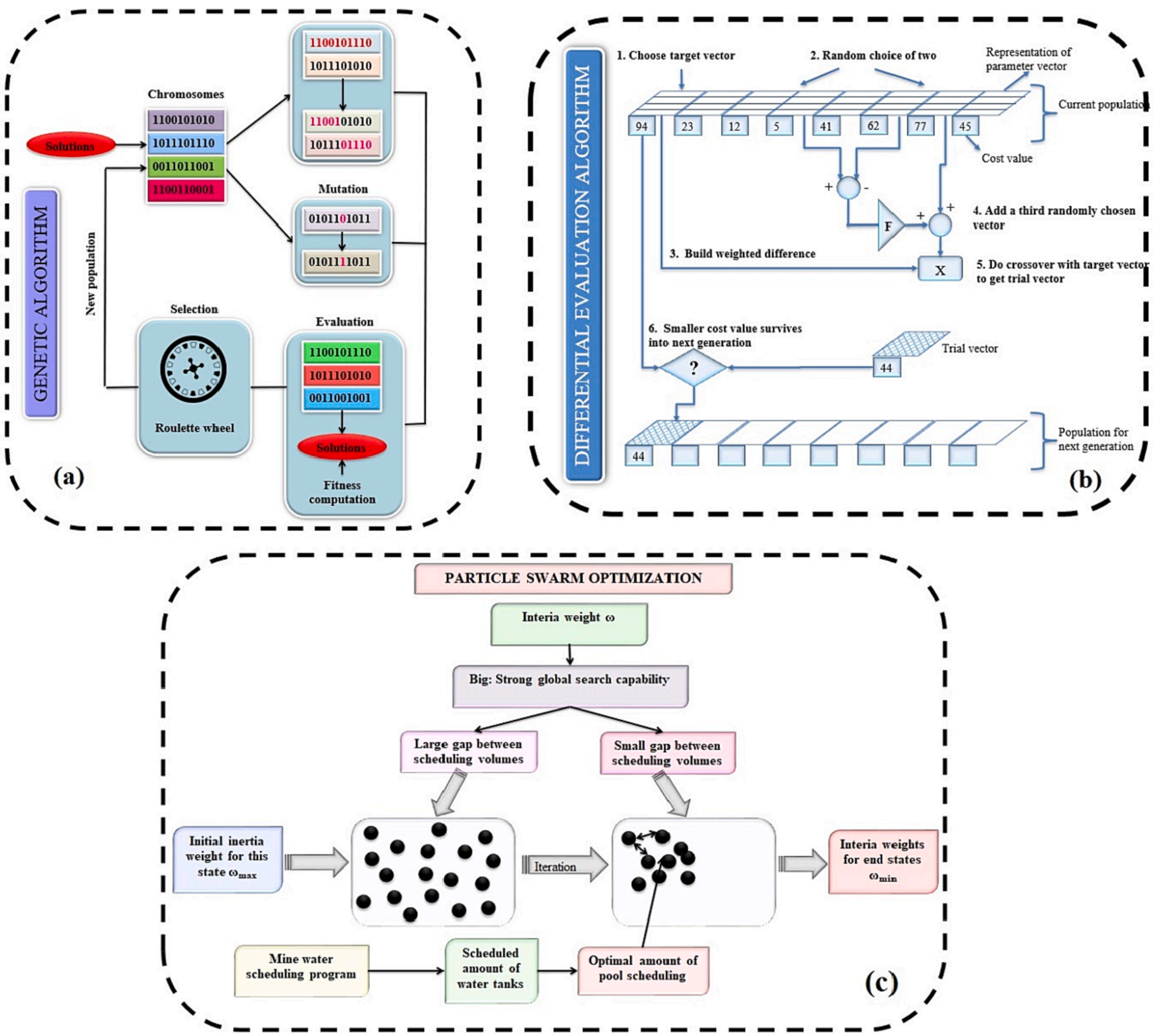

Fig. 4. Schematic presentation of genetic algorithm (a), differential evaluation algorithm (b), and particle swarm optimization (c).

selection), and (*viii*) a system that allows the best individuals to pass on their characteristics directly to future generations and is performed based on the elitism ratio (elitism).

In addition to its advantages such as being able to work on large and complex solution spaces, being easily adaptable to different problems, and having a multi-purpose function, GA also includes some shortcomings such as fitness function determination problem, early convergence problem, giving only near-optimum solutions (for problems with continuous or mixed variables), not good at identifying local optimum, needs to be combined with another local search algorithm, having very large number of functions to evaluate, having a large number of parameters to be determined (like the size of the population, mutation rate, crossover rate, and the selection method) (Chen and Chen, 1997).

5.2. Differential evaluation algorithm

DEA is an artificial intelligence technique that is not used very often in modeling compost parameters. DEA is also a popular evolutionary algorithm inspired by Darwin's theory of evolution (Ahmad et al., 2022). DEA executes four sequential procedures as initialization, mutation, crossover, and selection. The initialization stage is realized just a one-time in the process. The other three procedures are iteratively repeated in the search process of DEA until the termination criteria are satisfied. Although DEA is generally more successful in optimizing continuous-valued variables compared to GA, it still has some weaknesses such as having a complex procedure, unstable convergence, and poor search capability (Wang and Zhao, 2013; Wu et al., 2011). An illustration of DEA was given in Fig. 4(b). While these AI techniques are sometimes used to optimize the process parameters of classification or regression problems carried out by ML methods, the techniques are sometimes used to optimize the parameters. Dragoi et al. (2021) used DEA to train the ANN to predict TPH and OC (Dragoi et al., 2021).

5.3. Particle swarm optimization

Kennedy and Eberhart (1995) proposed another AI optimization technique named particle swarm optimization (Kennedy and Eberhart, 1995). PSO is a population-based heuristic algorithm that works with an iterative procedure (Fig. 4(c)). Although PSO has not yet been used in the studies for modeling the compost process parameters, has been used in many areas such as the modelling and optimization of Fenton processes (Cüce et al., 2021). PSO replicates the behaviour of natural flocks such as shoals and flocks of birds. The outstanding feature of PSO is that it can obtain a global optimum solution by simultaneously examining different points in different regions of the solution space. The inertia and acceleration parameters are iteratively adapted during the search process. PSO is based on approximating the position of individuals in the swarm to the best-positioned individual in the swarm. Consequently, the search space is explored by making use of both individual and social information originating from all swarm. Although PSO has important superior features compared to other heuristic optimization algorithms such as being easy in concept, coding implementation and having a limited number of parameters, it also has some fundamental shortcomings such as not having a solid mathematical foundation and longer computation time (Lee and Park, 2006).

AI optimization algorithms have been used as learning algorithms in the training process of ML algorithms, which are generally used for the prediction of composting process parameters. In this context, these studies linked and integrated ML and AI algorithms. A trained ML model is actually an estimate of the functional structure between the input and output parameters of the composting process. In some other studies, AI optimization algorithms were used independently of ML algorithms to find the optimum parameter values that produced the output of the composting process trained with traditional ML algorithms. GA has been used in many studies to optimize the composting process and parameters (Alavi et al., 2019; Bayındır et al., 2022; Kabak et al., 2022; Yılmaz et al., 2022).

6. Holistic perspective for ML and AI techniques in composting

Modeling, predicting and optimizing the process parameters are momentous in the composting process as in all waste management process. Accurate modeling, consistent predictions, and reliable optimization are priceless for producing solutions and decision-making processes. This can be achieved by choosing a proper and satisfactory modeling and optimization tool. Especially in recent years, researchers have preferred ML and AI algorithms for composting process. While ML algorithms have produced very valid results in the predictive modeling of composting process parameters, AI algorithms have been used for optimization of composting process parameters. Although all ML and AI tools have produced effective results, these tools also contain some difficulties and issues in the structures with the examination from a holistic critical perspective. Although all ML and AI tools have produced effective results, it is seen that these tools contain some difficulties and problems in their structure. In the studies that use ML and AI algorithms in the composting process, the results of estimation and modeling are focused on from the perspective of a practitioner. The disadvantages of these algorithms, the conditions of use, the problems that may arise in the absence of these conditions have not been discussed and ignored.

The studies in which ML and AI techniques were used in the composting process were examined from a holistic perspective in terms of data, relationship structure, hyperparameter tuning, reliability and validity, error metrics and optimization, and the challenges in the further development were summarized below.

Data overview, in all studies except one, fuzzy logic perspective was not used in terms of approaching uncertainty in the analysis of data sets that emerged during the composting process. The data obtained in composting problems contain uncertainty, and in this case, providing fuzzy approaches to uncertainty such as fuzzy regression and fuzzy regression functions will help to obtain more realistic and accurate results.

Relation structure overview, almost all of the studies in the field have accepted the relationships between the parameters that make up the process and the factors affecting these parameters as either only linear or only non-linear and used methods that can solve only one of them. However, due to the nature of the composting process, related relationships can exist together in both linear and non-linear structures in data. Modeling tools that can analyse both linear and non-linear relationships together, or the use of hybrid or ensemble models that can be created in this direction, can be recommended.

Hyperparameter tuning overview, hyperparameters are determined by the trial-and-error method in most of the studies using ML models in the composting literature. However, identifying these with analytical and/or methodological approaches such as cross-validation will bring model performance to the fore, especially for out-of-sample data sets.

Reliability and validity overview, it is a known that almost all ML models give different results under different initial conditions. Except for a few studies in the field of composting, it is recommended to run the models several times under different initial conditions to determine their level of validity and reliability.

Error metrics overview, benchmarks via some metrics such as RMSE, which are an indicator of which model outperforms, can be carried out. However, these cannot reveal the individual success level and cannot measure the performance level of the upper model. Although error metrics have been widely used in ML models in the field of composting, many studies did not use an error criterion such as MAPE that would reveal the individual success level in the evaluation of the results.

Optimization overview, the concept of optimization in the composting process is based on either optimizing the ML parameters used or evaluating the process parameters based on experimental designs without using any algorithms. In only a few studies, tools were used to determine the parameter values that will produce the process outputs at the desired level with an analytical approach. This will ensure that desired results are obtained with a small number of experiments to be designed with the specified parameter values, especially in cases where it is difficult and/or costly to conduct a large number of new experiments.

As a result, the following recommendations are presented for future studies on the use of ML and AI in modeling and optimization of the composting process: (*i*) the relationships found in the data should be examined as linear or non-linear structures, (*ii*) hyperparameter tuning should be performed at an appropriate and satisfactory size, (*iii*) model performance is highly affected by initial conditions, and it is necessary to investigate this and bring to light the validity and consistency of the models, (*iv*) the selection of metrics used in performance evaluation should be made with a metric that directly and accurately reflects performance, (*v*) parameter optimization should not be evaluated as training ML algorithms, but as the process of determining appropriate parameter values that will optimize process outputs, (*vi*) different ML algorithms succeed in different composting processes makes it difficult to talk about a dominant algorithm in general, due to their data-driven properties, (*vii*) different ANN types are more commonly preferred in the modeling composting process parameters than other ML algorithms and produce satisfactory results.

7. Conclusion

This review evaluated the advantages and limitations of different ML and AI algorithms used in the composting process, which is an important bioprocess. In the composting process, most of the ML work is pilot-scale and laboratory studies and is in the research and development stage. This study, with all its content, in addition to examining in detail the studies using ML and AI algorithms in the field of composting, emphasized their deficient and challenging aspects and formed a comprehensive reference for studies that will produce more realistic results in the future.

CRediT authorship contribution statement

Fulya Aydin Temel: Data curation, Visualization, Investigation, Writing – review & editing. **Özge Cagcag Yolcu:** Data curation, Formal analysis, Investigation, Writing – review & editing. **Nurdan Gamze Turan:** Supervision, Investigation, Writing – review & editing, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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