Environ Monit Assess (2024) 196:309
https://doi.org/10.1007/s10661-024-12443-2

REVIEW

# Artificial intelligence methods for modeling gasification of waste biomass: a review

**Fatma Alfarra · H. Kurtulus Ozcan · Pınar Cihan · Atakan Ongen · Senem Yazici Guvenc · Mirac Nur Ciner**

Received: 6 April 2023 / Accepted: 12 February 2024 / Published online: 26 February 2024


**Abstract** Gasification is a highly promising thermochemical process that shows considerable potential for the efficient conversion of waste biomass into syngas. The assessment of the feasibility and comparative advantages of different biomass and waste gasification schemes is contingent upon a multifaceted combination of interrelated criteria. Conventional analytical approaches employed to facilitate decision-making rely on a multitude of inadequately defined parameters. Consequently, substantial efforts have been directed toward enhancing the efficiency and productivity of thermochemical conversion processes. In recent times, artificial intelligence (AI)-based models and algorithms have gained prominence, serving as indispensable tools for expediting these processes and formulating strategies to address the growing demand for energy. Notably, machine learning (ML) and deep learning (DL) have emerged as cutting-edge AI models, demonstrating exceptional effectiveness and profound relevance in the realm of thermochemical conversion systems. This study provides an overview of the machine learning (ML) and deep learning (DL) approaches utilized during gasification and evaluates their benefits and drawbacks. Many industries and applications related to energy conversion systems use AI algorithms. Predicting the output of conversion systems and subjects linked to optimization are two of this science's critical applications. This review sheds light on the burgeoning utility of AI, particularly ML and DL, which have garnered significant attention due to their applications in productivity prediction, process optimization, real-time process monitoring, and control. Furthermore, the integration of hybrid models has become commonplace, primarily owing to their demonstrated success in modeling and optimization tasks. Importantly, the adoption of these algorithms significantly enhances the model's capability to tackle intricate challenges, as DL methodologies have evolved to offer heightened accuracy and reduced susceptibility to errors. Within the scope of this study, an exhaustive exploration of ML

F. Alfarra (✉) · H. K. Ozcan · A. Ongen · M. N. Ciner
Engineering Faculty, Department of Environmental Engineering, Istanbul University-Cerrahpasa, 34320 Avcilar, Istanbul, Turkey
e-mail: mayafarra90@gmail.com

H. K. Ozcan
e-mail: hkozcan@iuc.edu.tr

A. Ongen
e-mail: aongen@iuc.edu.tr

M. N. Ciner
e-mail: mirac.ciner@iuc.edu.tr

P. Cihan
Corlu Engineering Faculty, Department of Computer Engineering, Tekirdag Namık Kemal Universtiy, 59860 Çorlu, Tekirdag, Turkey
e-mail: pkaya@nku.edu.tr

S. Y. Guvenc
Department of Environmental Engineering, Faculty of Civil Engineering, Yildiz Technical University, Davutpasa Campus, 34220 Istanbul, Turkey
e-mail: syazici@yildiz.edu.tr

and DL techniques and their applications has been conducted, uncovering existing research knowledge gaps. Based on a comprehensive critical analysis, this review offers recommendations for future research directions, accentuating the pivotal findings and conclusions derived from the study.

**Keywords** Gasification · Artificial intelligence · Machine learning · Deep learning · Hybrid model · Optimization

## Introduction

Many challenges face the world these days, including an expanding population, rising energy consumption, problems with climate change, and environmental contamination. Around 80% of the world's energy is produced by fossil fuels like natural gas, petroleum, and coal (Umenweke et al., 2022). Because of the growing population, in the next two decades, the demand for fossil fuel energy is predicted to rise by about 35% (Lachos-Perez et al., 2022). Generating clean and sustainable fuels is one of the significant challenges to addressing future energy crises and minimizing the consequences of climate change by reducing greenhouse gas emissions (Nunes, 2022). Since more is being done to reach net-zero emissions, there is already a greater need for additional renewable energy sources that come from co-gasifying biomass (Ayodele et al., 2022). Because of a worldwide commitment to decrease global warming, the necessity for advanced biofuels generated from environmentally friendly sources is stressed nationally and internationally. The two primary objectives of the Norwegian climate agreement are to reach climate neutrality by 2030 and to have a society with zero emissions by 2050 (Norwegian Ministry of Climate and Environment (NMCE), 2019). The rising global energy demand and environmental protection trends also require seeking alternatives to petroleum products (Ugwu et al., 2022). It is crucial to find energy sources that are economical and environmentally friendly due to decreasing fossil energy supplies, rising fuel costs, and environmental issues (Khan et al., 2023).

Today, technologies could provide viable alternatives to conventional fuel systems based on coal, oil, or natural gas (Asadi et al., 2020). Renewable energy sources are many, including biomass, hydro, solar, wave, geothermal, and eolian, as well as varying levels of accessibility, possibility, and development of technology (Nunes, 2022). From the abovementioned alternatives, biomass energy is only unconfined by availability or accessibility issues (Zalazar-Garcia et al., 2022). As a possible renewable energy source, bioenergy can replace fossil fuels. The progress of sustainable waste management seeking a circular economy and carbon neutrality becomes possible with bioenergy recovery from waste (khan et al., 2023). According to International Energy Agency (IEA), in, 2019, bioenergy contributed nearly 70% of the renewable energy used in 2016; solid biofuels accounted for 62% of total bioenergy, liquid biofuels accounted for 4.5%, biogas accounted for 1.7%, and renewable municipal wastes accounted for roughly 1%. From 1990 to 2016, growth rates for biogases and liquid biofuels were 12% and 10%, respectively (IEA, 2019). Generally speaking, biomass is a carbon–neutral resource that may be used to generate heat, power, and essential compounds like $H_2$, CO, and $CH_4$. Producing biofuels from waste biomass could decrease the effects of climate change and environmental issues (Umenweke et al., 2022). The two primary categories of biomass processes for converting energy are biochemical and thermochemical. Specified products are produced by biochemical conversion processes, including biogas and ethanol; the conversion process is generally slower and can take several hours, days, or weeks (Seo et al., 2022). However, the economic utilization of biomass in thermal conversion procedures has really been understated; due to the additional price of biomass than fossil fuels and other unaddressed biomass challenges, like high amounts of moisture (>40 wt%), low lower heating value (3,000 MJ/kg), and low conversion rates (Seo et al., 2022). Table 1 describes the processes for bioenergy conversion (Halba et al., 2022). Thermochemical processing is a technique for the future that carries a lot of hope.

It has recently gained a lot of attention due to its adaptability in handling feedstock, faster reaction periods, minimal investment costs, range of results, higher processing productivity, $CO_2$ neutral, and quality enhancement of products (W. H. Chen et al., 2021). In order to create value-added solids, liquids, and gases compounds, thermochemical technologies like pyrolysis, torrefaction, hydrothermal,

**Table 1** The biomass conversion technology

| Technology | Method | Product | Advantages | Disadvantages | Reference |
|---|---|---|---|---|---|
| Thermochemical conversion | Gasification | • Producer gas<br>• Char | • Possibility of supplanting the coal-based power plant<br>• Producing fewer emissions as compared to waste-disposal combustion plants<br>• Produce high-quality biochar | • A powerful technique for removing tar from producing gas<br>• High investment cost | (Halba et al., 2022; Salem et al., 2022) |
| | Pyrolysis | • Pyrolysis oil<br>• Producer gas<br>• Char | • Converting low-energy biomass into liquid fuels with a high energy density<br>• Possibility of producing chemicals using bio-based materials | • The great viscosity of pyrolysis oil may make it difficult to transfer and combust<br>• When dealing with wastes that contain a lot of moisture, net energy recovery could be reduced | (Chu et al., 2023b; K. Mishra et al., 2023) |
| | Torrefaction | • Solid biofuel | • Improved grindability and bulk density<br>• A higher calorific value<br>• Homogeneous as well as hydrophobic biomass | • A significant energy input<br>• To reduce the loss of chemical energy, excellent process control is necessary<br>• High capital costs | (Kong et al., 2022; Manatura et al., 2023) |
| | Combustion | • Heat<br>• Electricity | • The simplest method of generating energy<br>• Produce a comparatively inexpensive fuel source<br>• Minimizes the demand for fossil fuels | • Releasing more greenhouse gases than other bioenergy processes<br>• It needs water to keep the engine cool<br>• Low effectiveness | (Kartal and Özveren, 2022a; Li et al., 2023a) |
| | Liquefaction | • Biofuel<br>• Syngas<br>• Liquid fuels | • Compared to raw biomass, the calorific value increased from around 15 MJ/kg to about 35 MJ/kg for bio-crude<br>• Aromatics and subtle hydrocarbons are produced from fossil sources | • Oxygenated compounds have a high viscosity<br>• A major upgrade is necessary since the calorific value remains poor compared to fossil fuels | (Liu et al., 2023d; Qian et al., 2023; Yang et al., 2023) |

**Table 1** (continued)

| Technology | Method | Product | Advantages | Disadvantages | Reference |
|---|---|---|---|---|---|
| Biochemical conversion | Anaerobic digestion | • Fertilizer<br>• Liquid fuels<br>• Biogas<br>• Electricity | • Enhancement of soil health<br>• Reduction of methane emissions<br>• Appropriate for wet biomass | • Problems with foaming and over-acidification<br>• Take longer than other methods to produce bioenergy | (Pomeroy et al., 2022; Saravanan et al., 2023; Zhai et al., 2020) |
| | Fermentation | • Liquid fuels (bioethanol) | • Regardless of the quality of the biomass, use the whole biomass, including the lignin<br>• The removal of costly and difficult pre-treatment procedures | • The gas substrata have bad mass transmission characteristics<br>• Reduced biocatalytic ethanol production | (Chilakamarry et al., 2022; Vinitha et al., 2022) |

gasification, as well as combustion were employed (Khan et al., 2023). A general overview of the thermochemical technologies has been presented in Fig. 1.

In the technology of pyrolysis, the biomass feedstock is transferred into three products (bio-oil, biochar, and pyrolytic gas) without the presence of air at temperatures between 300 and 650 °C. Also, if bio-oil is processed correctly, it could substitute fossil fuels (Tang et al., 2020). At pressure of atmosphere in the non-existence of $O_2$ and temperatures ranging between 200 to 320 °C, organic matter is torrefied to generate bio- coal (García Nieto et al., 2019). Hydrothermal process is considered one of the most advanced processes since it can treat biomass feedstocks in the presence of moisture. This process is achieved between 5—20 MPa of pressure and 200—350 °C of temperatures. According to the required outputs, such as biogas, bio-oil, or bio-carbon, the process's temperature, pressure, and time are established (Shafizadeh et al., 2022). During combustion, biomass is burned in extra air, causing a number of chemical processes that result in the production of heat (Z.-H. Zheng et al., 2020). Gasification is another well-known thermochemical process under extreme temps between 500 to 1000 °C, the biomass is transformed into synthesis gas in the existence of a gasification agent (Nunes, 2022). In terms of cost-effectiveness and environmental friendliness, gasification is an essential technology for generating energy and other chemicals. Biomass is converted into gasiform fuels by warming it in $O_2$-rich air, $CO_2$, steam, air, or a combination of these agents. Syngas mainly comprises $H_2$, CO, $CO_2$, $N_2$, and little hydrocarbons. It is also possible to find traces of tars, $NH_3$, and $H_2S$ (Kartal & Özveren, 2022b). Gasification involves complicated thermochemical reactions that occur impacted by a broad range of elements, for example, type of biomass, reaction temperature, catalyst use, type of gasification agents, and size of particles. (Fang et al., 2022). Even though biomass gasification is efficient, renewable, and eco-friendly, it requires a significant investment and has high operating costs. In addition, this exothermic process also generates a considerable amount of thermal energy while operating at high temperatures. To improve its sustainability, it is necessary to efficiently manage the thermal energy generated and consumed during the process (Y. Zhang et al., 2019). During gasification,

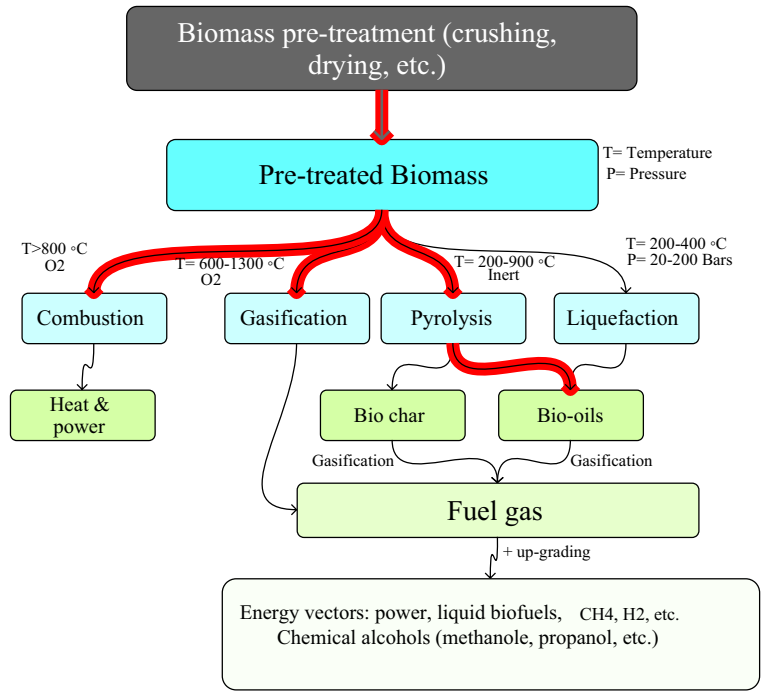



**Fig. 1** Outline of the general thermochemical technologies

many factors are able to influence the quality and quantity of the results, such as biomass composition and process parameters.

Consequently, more experiments should be done to hydrogen-rich syngas production, improve syngas yield, and enhance its quality (Ayodele et al., 2022). The complicated interaction between components impacting biomass degradation makes it difficult to realize the formation of synthesis gas within gasification, at the same time, is costly and time-consuming (Umenweke et al., 2022). Furthermore, simulating gasification processes could offer thorough details and insights into the mechanisms of the reaction. Real-time process control may be achieved, and the required output parameters can be correlated with the assistance of modeling a process (Aghbashlo et al., 2021). The complicated chemical processes that occur during gasification, and the mass and heat transport within the reactors, have all been modeled using various techniques. Historically, computational fluid dynamics (CFD), kinetic, and thermodynamical models have been given the greatest focus. Those processes can demonstrate the fundamental principles controlling the reactions in gasification. However, they are costly and require complex calculations (Ascher et al., 2022a, b; Zhao et al., 2022). Even though thermodynamical study is economical as well as easy, achieving the conditions in a practical gasifier is problematic, as a result, forecasting efficiency is negatively impacted. Additionally, A kinematic assessment requires considerable time to formulate (Li et al., 2020).

Artificial intelligence (AI)-based algorithms were created to effectively predict systems' output through learning and mining system characteristics using minimal experiment data to cope with this difficulty. Thus, AI-based solutions can help learn biomass gasification's fundamental principles and traits (Forootan et al., 2022; Mutlu & Yucel, 2018). Artificial intelligence serves as the main system. Machine learning (ML) is considered to be a subfield within the more general field of AI. Deep learning (DL) is a specific field inside the broader subject of machine learning, wherein neural networks serve as the basic foundations for DL algorithms. In recent years, the usage of AI has risen exponentially (K. Lin et al., 2022). ML approach includes conventional ML models, for instance, artificial neural networks (ANNs), decision trees (DT), random forests (RF), gradient boost regressors (GBR), support vector machines (SVM), etc.; similarly, the DL approach includes convolutional

neural networks (CNNs), long short-term memory (LSTM), generative adversarial networks (GANs), etc. Figure 2 shows the relation among DL, ML, NN, and AI.

Recent advances in DL have made it possible to use it to improve the performance of gasification due to recent achievements in natural language processing (NLP) and image processing (Da'u and Salim, 2020). Additionally, a DL method was set to forecast the rate of $CO_2$ adsorbed on zeolites (Mahmoud et al., 2022). However, despite these efforts, little research has been carried out on gasification. Moreover, DL models such as CNNs have been utilized to detect Alzheimer's disease (E. Lin et al., 2021), to better the management of e-waste collecting (Nowakowski & Pamuła, 2020), also used to forecast flow behavior in solutions of heavy particulates (Ashwin et al., 2022). Additionally, Nam et al. (2020) used DL for renewables forecasts. Nearly all fields could use DL applications (Alom et al., 2019). Using the proper ML approach, it is possible to simulate the complicated non-linear interaction among the forecasters and the intended result (Bahadar et al., 2022). In recent times artificial intelligence algorithms have been quickly developed and employed. ANNs and other ML approaches have attracted significant attention because of their capability to efficiently simulate

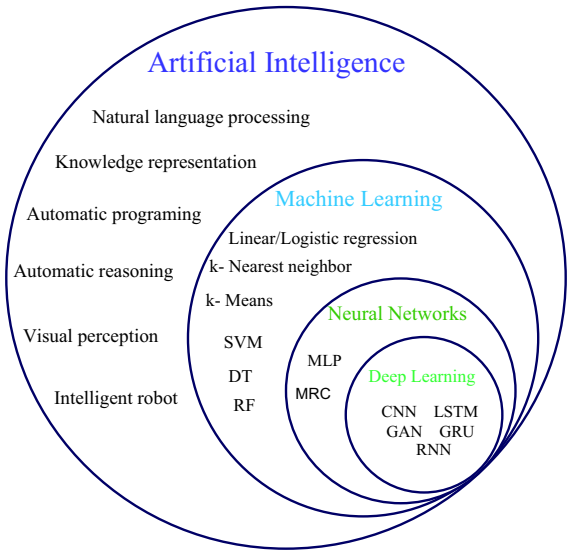



**Fig. 2** Relation among AI, ML, NN, DL

these very complicated processes (Ascher et al., 2022a, b; Zhao et al., 2022).

Unlike kinetics and thermodynamics methods, ML models utilize factual circumstances of experimentation to estimate the yield of hydrogen perfectly with no statements or time constraints and exhibit the impact of input parameters on gasification (Li et al., 2020). From this perspective, ML techniques like ANN, RF, GBR, and SVM have recently been used in many studies to improve the thermal conversion of biomass (Hashem Samadi et al., 2023; Jamro et al., 2023; Kim et al., 2023; S. Liu et al., 2022; Ozbas et al., 2019). For example, to forecast the $H_2$ yield from biomass gasification based on various parameters, including heating value, temperature, time, $CO_2$, CO, $O_2$, and $CH_4$, Ozbas et al. (2019) used decision trees regression (DTR), support vector machine regression (SVMR), Linear Regression (LR), and K nearest neighbors (KNN) regression algorithms. Jamro et al. (2023) used an ANN-based ML model to predict $H_2$ yield. A multilayer perceptron (MLP)-NN model was developed by Hashem Samadi et al. (2023) to forecast the syngas composition and lower heating value (LHV) of the gas during gasification. Similarly, RF, SVM, and ANN models were employed to estimate synthesis gas composition and LHV using biomass gasification (Kim et al., 2023). Additionally, S. Liu et al. (2022) applied GBR, RF, DT, and ANN models to predict the syngas yield when employing hydrothermal gasification (HTG). On the other hand, several review articles have been published on biomass gasification modeling. One of these studies examined the application of machine learning (ML) technology in conventional and HTG research. Furthermore, a brief discussion of the ANN, SVM, DT, and deep neural network algorithms applied to gasification studies was included (Umenweke et al., 2022). Another review compared the ML model's accuracy and provided insights into the parameters that were utilized to inform the models and make predictions. This article has addressed the gasification systems utilized by ML models and waste- to-energy methods, especially ANNs and GBR (Sedej et al., 2022).

Energy demand similarly, DL techniques such as LTSM have been used by (Khurram Faridi et al., 2022) to predict the Spatio-temporal temperature, additionally gated recurrent unit (GRU) based recurrent neural network (RNN) model was used to forecast the reactant and product compositions (K. G.

Sharma et al., 2022). Finally, the applicability of several ML algorithms (ANN, SVM, DT, RF, etc.) DL algorithms (LTSM, GRU, CNN, etc.) and hybrid models (ANN-PSO, ANN-AdaBoost, RF-GA, etc.) for thermochemical conversion processes have been discussed, as well as their advantages and disadvantages (Khan et al., 2023). It is impossible to fully describe this wide and dynamic field in a few review papers. So, other ML methods should be included in subsequent reviews. In this regard, the proposed article compares different ML and DL algorithms for various applications, discusses their advantages and disadvantages, and provides insights into the future directions of modeling gasification via ML and DL methods.

Our review is designed as follows: The first part looks at thermochemical techniques for converting biomass and waste and provides an overview of the gasification processes. The second part provides an overview of the ML and DL approaches utilized during gasification and evaluates their benefits and drawbacks. The third part examines the methods researchers have employed to model gasification processes using ML and DL approaches. Fourth Part briefly describes the current and future challenges in the ML and DL approaches. Finally, the outcomes of this study are summed up in part fifth.

## Gasification processes and technologies

### Gasification process overview

Increasing waste production has led to the need for a quick solution. The current approach to waste management relies on converting it into valuable products. Therefore, biomass has gained economic significance (Saravanan et al., 2023). Due to their favorable environmental and economic effects, waste-derived renewable fuels are gaining popularity worldwide. Their various components are at high temps (500–1400 °C) and pressures (up to 33 °C) (Ajorloo et al., 2022). Syngas can be converted into value-added chemicals or used for cogeneration to generate electricity. Drying, pyrolysis, combustion, cracking, and reduction are the steps during gasification (Ascher et al., 2022a). Figure 3 shows the biomass gasification process.

Equations 1 to 8 illustrate the significant reactions that occur through gasification (Sansaniwal et al., 2017).

$$\text{Drying reaction}: \text{Moist raw material} + \text{heat} \rightarrow \text{dry raw material} + H_2O \quad (1)$$

$$\text{Pyrolysis reaction}: \text{Dry raw material} + \text{heat} \rightarrow \text{coal} + \text{volatiles} \quad (2)$$

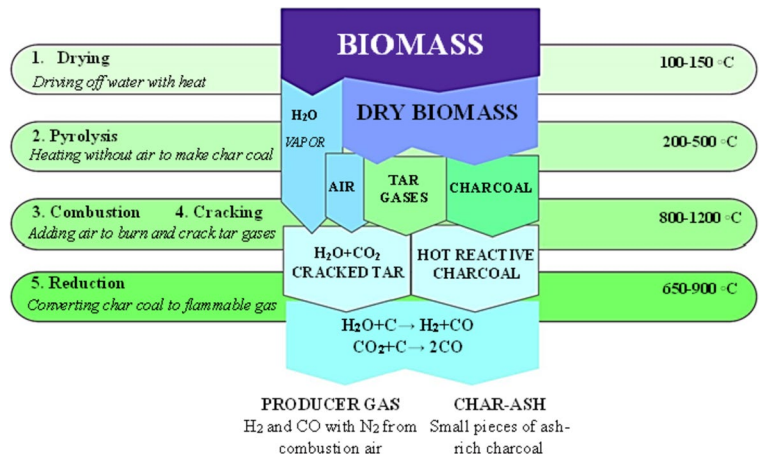



**Fig. 3** The five processes of gasification

$$\text{Oxidation reactions}: C + O_2 \rightarrow CO_2 + 406\text{kJ/g.mol} \quad (3)$$

$$2C + O_2 \rightarrow 2CO - 123\text{kJ/g.mol} \quad (4)$$

$$\text{Reduction reactions}: C + CO_2 \rightarrow 2CO - 172.6\text{kJ/g.mol} \quad (5)$$

$$C + H_2O \rightarrow CO + H_2 - 131.4\text{kJ/g.mol} \quad (6)$$

$$C + 2H_2 \rightarrow CH4 + 75\text{kJ/g.mol} \quad (7)$$

$$CO + H_2O \rightarrow CO_2 + H_2 + 42.3\text{kJ/g.mol} \quad (8)$$

Several indicators, including the syngas component, heating value, carbon conversion efficiency, and ash concentration, may be utilized to evaluate the effectiveness of gasification (Ajorloo et al., 2022). In general, the operational parameters, gasifier types, pressure, speed, gasifying agents, fuel elements, catalytic efficiency, temp, etc., all influence the production and content of synthesis gas (Tezer et al., 2022). Gasifying agents significantly influence the content of synthesis gas as well as feedstock reaction. To attain the necessary syngas quality during the gasification process, $O_2$, $CO_2$, air, steam, or their mixes might be employed. Table 2 summarizes the advantages and disadvantages of the most commonly used gasifying agents for biomass gasification (Shahbeig et al., 2022).

## Biomass gasification technologies

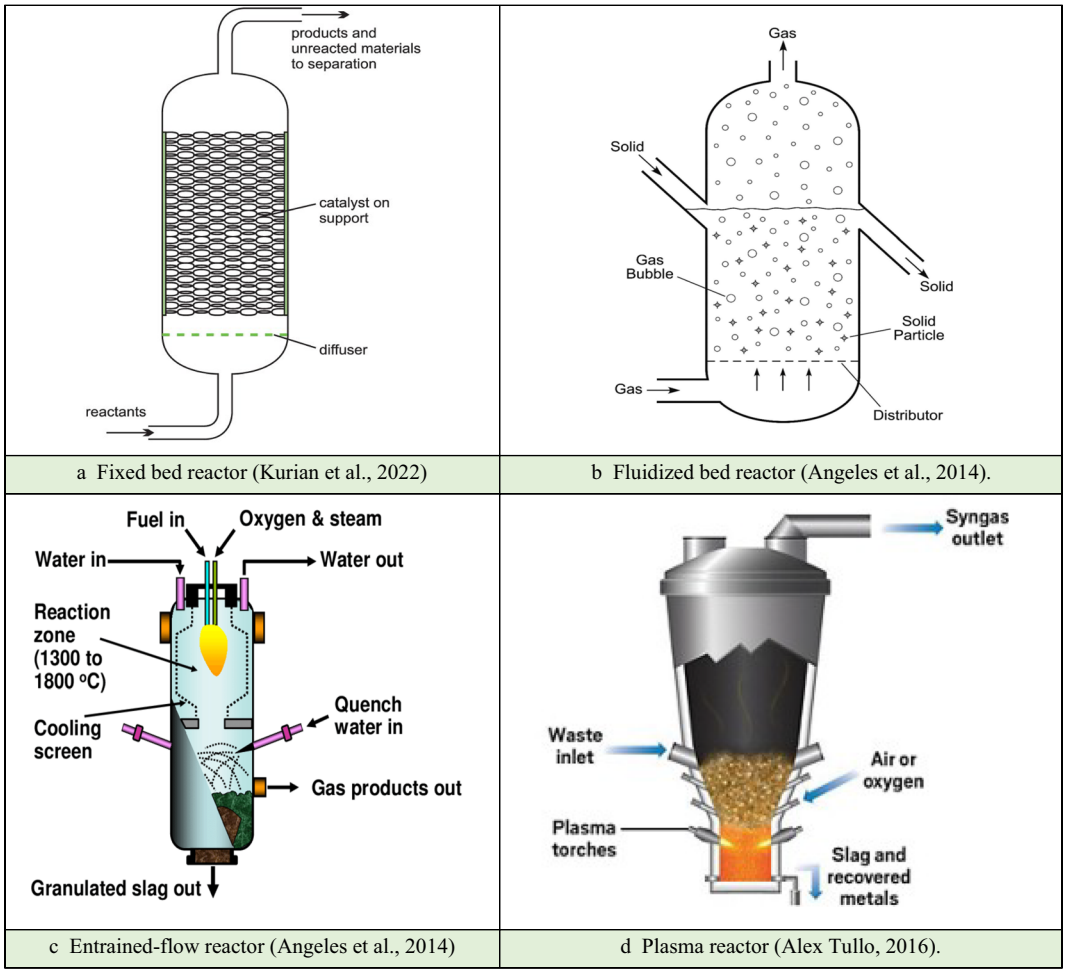
Gasification can be carried out in a number of different reactor designs. Fixed bed, fluidized bed, entrained-flow reactors, and plasma reactors are all examples of gasifiers used in the gasification process. Figure 4 illustrates the schematic representation of these gasifiers. The gasifying agent, temperature, pressure, transport procedure, heat supply technique, and bed material type are all factors in gasifier design (Maitlo et al., 2022; S. Mishra & Upadhyay, 2021; Tezer et al., 2022).

### *Fixed-bed (updraft, downdraft, cross-draft)*

The gas and gasifying medium in fixed-bed gasifiers are either rising (updraft), descending (downdraft), or flowing horizontally through the reactor (cross-draft). Also, the reactor has a bed of solid fuel particles (Cortazar et al., 2023). As gasifying media, one or more air, steam, oxygen, or a mix of these can be employed. Compared to fluidized bed alternatives, fixed-bed gasifiers often produce a clean product gas with little dust and tar while being substantially more affordable for more minor purposes. These are its two main practical advantages (Kushwah et al., 2022). The major limitation is having lower heat transfer and temperature homogeneity. Furthermore, fixed-bed gasifiers often have more strict feed requirements, such as humidity levels (under 20%) and homogeneous particle sizes (to prevent clogging and channeling) (Safarian et al., 2019).

**Table 2** Advantages and disadvantages of gasifying agents (Maitlo et al., 2022; Shahbeig et al., 2022; Sidek et al., 2020)

| Agents | Advantages | Disadvantages |
|---|---|---|
| Air | • Easy process<br>• Technological advance<br>• Normal char level<br>• Little formation of ash | • Smaller levels of CO and $H_2$<br>• Smaller synthesis gas effectiveness<br>• Increase in nitrogenous substances<br>• Greater cleanup expenses |
| $O_2$ | • Technological advance<br>• Small char production<br>• Quality synthesis gas<br>• Smaller reaction temperature | • Greater investment and operating costs<br>• Greater process complication<br>• Possible risks related to tanks |
| $CO_2$ | • Greater synthesis gas production<br>• Reduced Carbon dioxide releases<br>• Greater process effectiveness | • Greater generation of char<br>• Longer reaction time |
| Steam | • Greater carbon conversion<br>• Greater synthesis gas production<br>• Greater synthesis gas quality<br>• Greater effectiveness | • More energy wasted<br>• More tar generation |




a Fixed bed reactor (Kurian et al., 2022)

b Fluidized bed reactor (Angeles et al., 2014).

c Entrained-flow reactor (Angeles et al., 2014)

d Plasma reactor (Alex Tullo, 2016).

**Fig. 4** Types of gasifiers

*The fluidized bed (bubbling, circulating)*

Typically, in this technology, a fluid flows through a cylindrical column of particles (Safarian et al., 2019). Based on fluidization principles, fluidized beds have a high degree of the mix, accelerating the process and improving efficiency. Heat and mass transfer efficiency is also enhanced, resulting in great operational flexibility and bed isothermic. So, for large-scale applications, this technology is more attractive and cost-effective (Cortazar et al., 2023). The high amount of dust in the syngas is a significant disadvantage of fluidized bed gasifiers, which could be problematic for downstream equipment (Safarian et al., 2019).

*Entrained-flow reactors*

Entrained flow reactors running at 20–70 bar pressure is among the most effective gasifiers. They are well-suited for industrial use because of their high carbon conversion efficiency (almost 100%) (S. Mishra & Upadhyay, 2021). These gasifiers operate at temperatures from 1300 to 1500 °C, making them ideal for the cracking of tar. The type of biomass used as fuel is the primary factor in establishing the final temperature (Lian et al., 2021; Maitlo et al., 2022). Furthermore, it should be noted that the residence period in these reactors is quite short due to their exceptional efficiency and the reduced methane content observed in the gas that is discharged from the outlet. The entrained flow gasifier operates using

co-current reactors, wherein biomass fuel, in the form of small particles or slurry, is introduced alongside a gasifying agent into the reactor (Mazzoni et al., 2020; Shahabuddin & Alam, 2022). The process described leads to the entrainment of particles as they traverse the compact cloud. The gas is extracted from either the upper or lower section, while the slag or liquid ash is accumulated at the base. Nevertheless, the operation of these gasifiers at elevated temperatures presents challenges in terms of selecting appropriate materials and preventing ash from melting (Hameed et al., 2021; Lian et al., 2021).

*Plasma reactors*

Typically, a pair of copper or carbon electrodes are used in plasma gasifiers. Additionally, when the reactor's internal temperature reaches up to 10,000 °C, the plasma gasifier will deliver an electric charge commonly referred to as an "arc." (Hameed et al., 2021; Song et al., 2022). The process of atomic degradation of fuel occurs within gasifiers during the gasification process, which is carried out under various atmospheric conditions. The plasma process serves as the primary source of energy for the increase in biomass temperature in the absence of an oxidizing agent (Shahabuddin et al., 2020). The reactor has the capability to process many types of waste, including general, medical, and hazardous waste, and is able to achieve complete carbon conversion irrespective of the composition of the raw material. The plasma technique under consideration has the capability to attain exceedingly elevated temperatures, so facilitating the complete decomposition of raw materials into carbon monoxide (CO) and hydrogen ($H_2$), thereby generating a synthesis gas that is environmentally benign (Mazzoni et al., 2020; Shahabuddin et al., 2020). The utilization of increased plasma power leads to an elevation in the $H_2$/CO ratio, hence resulting in elevated temperatures and enhanced tar cracking. The higher heating value (HHV) of syngas generated varies between 6 and 7 MJ/Nm$^3$ under various operational circumstances. The findings indicate that the $H_2$/CO ratio generated is significantly greater compared to traditional reactors that employ air, oxygen, and steam as gasifying agents (Mazzoni et al., 2020; Song et al., 2022).

Related gasification studies

The increasing worldwide population has resulted in a significant rise in the need for energy and the production of waste. An effective strategy for addressing both energy demand and waste management concerns is the conversion of waste into energy, as emphasized by Alaedini et al. (2023). As a result, there has been a significant amount of research and experimentation conducted, specifically targeting the conversion of waste into energy, with a special focus on the gasification process.

Examining the findings of various studies reveals the persistent complexity associated with large-scale biofuel production. Addressing both present and future energy demands necessitates technical advancements to enhance the efficiency of biofuel production and optimize biomass management (Duc Bui et al., 2023; Liang et al., 2023; Mukherjee et al., 2023; Saeed et al., 2023). Concurrently, research on gasification primarily focuses on refining operating conditions by investigating the impact of diverse performance parameters on the gasification process (Asaad et al., 2023; Chu et al., 2023a, b; Papa et al., 2023). Moreover, attention has been directed toward minimizing tar formation (Fu et al., 2023), exploring the catalytic effects on biomass gasification (Qianshi et al., 2023; Y. Wu et al., 2022; Yim et al., 2023), and reviewing technologies for converting waste into hydrogen (Alaedini et al., 2023). Furthermore, studies highlight the utilization of Aspen Plus to optimize gasification operational parameters for the production of high-quality syngas (Kombe et al., 2022; Martins et al., 2023; Okati et al., 2022, 2023a, b). Finally, research explores the integration of gasification with various biomass conversion methods (Huang et al., 2023; Liu et al., 2023b, c, d; Yan et al., 2023; Yan et al., 2022; Yang et al., 2023; Ziółkowski et al., 2023).

Moreover, a few papers on comparative economic thermodynamic, techno-economic, and improving the conversion of healthcare waste (COVID-19) into hydrogen (Chalermsinsuwan et al., 2023; Li et al., 2023b), In order to compare CO and $H_2O$ gasification, the effects of char size of particles, as well as temperature affecting coal converting, have been investigated (C. Zheng et al., 2023). Furthermore,

**Table 3** Studies for the last research on gasification

| Feedstock | Gasification process | Reaction conditions | Agent | Results | Reference |
|---|---|---|---|---|---|
| Wood sawdust and PVC | Plasma | • Temp: 700–900 °C<br>• Steam/carbon ratio: 0–3.0<br>• Reactor type: fixed bed | Steam | Regarding the rate of carbon conversion, the proportion of $H_2$, and the ratio of chlorine release, temperature was the most essential factor | (Chu et al., 2023a) |
| Rice husk | Biomass gasification | • Temp: 700–900 °C<br>• Steam/carbon ratio: 0–3.0<br>• Reactor type: fluidized bed | Air | Gasification of biomass responded favorably to microwave treatment. At T 900 °C, the best syngas productivity, higher heating value, and cold gas efficiency | (Fu et al., 2023) |
| Corn straw | Biomass gasification | • Temp: 800 °C<br>• Reactor type: downdraft fixed bed | Air | Provided an effective way to recycle waste biomass ash, as it had a significant nutrient value | (Q. Guo et al., 2023) |
| Energy crops (Cynara cardunculus L. and Helianthus annuus L.) | Biomass gasification | • Temp:400–850 °C • Steam/carbon ratio (S/C): 1–3.0<br>• Reactor type: fixed bed | Steam and $CO_2$ | During $CO_2$ gasification, energy recovery from the crops was greatly improved | (Vamvuka et al., 2023) |
| Bamboo, peach wood, and wheat straw | Biomass gasification | • Temp: 900 °C<br>• Reactor type: horizontal quartz tube furnace | $CO_2$ | The coal's high porosity, large oxygen/carbon ratios, and reduced ash content in the biomass all contributed to better gasification effectiveness | (Mu et al., 2023) |
| Sewage sludge | Hydrothermal carbonization and $CO_2$ gasification | • Temp: 700–900 °C<br>• Reactor type: vertical tube furnace<br>Catalyst: Cao | $CO_2$ | The used procedure was a good method for handling sludge sustainably to produce quality syngas | (Huang et al., 2023) |
| Straw char | Chemical looping gasification | • Temp: 700–900 °C<br>• Reactor type: fixed bed<br>• Catalyst: $Fe2O_3$ and $MnFeO_3$ | Steam | The reaction temperature and steam flows were two factors that affect hydrogen-rich syngas generation<br>Using $Fe_3O_4$ resulted in the highest production of $H_2$ gas<br>$MnFe_2O_4$ contributed to improving the gas yield production | (Liu et al., 2023a) |
| Woody biomass | Biomass gasification | • Temp: 750–850 °C<br>• Reactor type: A stainless steel vertical<br>• Catalyst: acid mine drainage sludge ADMS | Air | The use of AMDS as a catalyst in gasification have the capability to both reduce the difficulties associated with AMDS treating and provide useful $H_2$-rich gas | (Yim et al., 2023) |

**Table 3** (continued)

| Feedstock | Gasification process | Reaction conditions | Agent | Results | Reference |
|---|---|---|---|---|---|
| Plastic waste | HTG | • Temp: 450–700 °C<br>• Reactor type: Quartz tube batch<br>• Pressure:22–29 MPa | ultrapure water | The gasification efficiency had significantly improved by temperature increase, prolonging time, and reducing feedstock concentration; however, pressure change had no obvious effect | (Lu et al., 2023) |

latest research as well discusses the use of various biomass sources and different thermochemical conversion techniques in producing hydrogen (Mishra et al., 2023; Sajid et al., 2022). Following microwave treatment, features of coal gasification with $CO_2$ were investigated (Dong et al., 2023), as syngas production (Jiang et al., 2023; Liu et al., 2023a, b, c, d). With gasification, various biomass could be transformed into a more efficient fuel which might subsequently be applied to heat and electricity generation. Consequently, Table 3 summarizes a sampling of recent research on the gasification of different waste biomass.

## Overview of machine learning and deep learning

A variety of distinct techniques consists of machine learning, which is often used in various fields. This interesting, rapidly developing technology is well known because of its creative use in speech recognition, self-driving cars, meteorology, natural language processing, image processing, as well as other fields. Recently ML has become more well-known in chemical research, including drug discovery, predictive toxicology, cheminformatics, environmental sustainability, green chemistry, and others (Umenweke et al., 2022). Machine learning techniques have been successfully used in fields related to the environment, like wastewater, solid waste treatments, and air pollution because of their superior capacity to simulate complicated systems (Ye et al., 2020). Machine learning is one of the most famous data analysis techniques in artificial intelligence. Supervised, semi-supervised, unsupervised, and reinforced learning are the four types of machine learning algorithms, as depicted in Fig. 5. During supervised learning, the algorithm is given the dataset and the matching outcomes. Following this, its algorithm develops a matching between the dataset and its outcome (Guan et al., 2022).

Methods of supervised learning include regression and classification methods. Both ways are used in ML predictions and work with labeled datasets. While classification methods aim to find behavioral patterns across datasets, regression methods look for the best-fit connection between the dependent and independent variables (Wang et al., 2021). Unsupervised machine learning ultimately depends on input data; the model learns by identifying patterns in the input

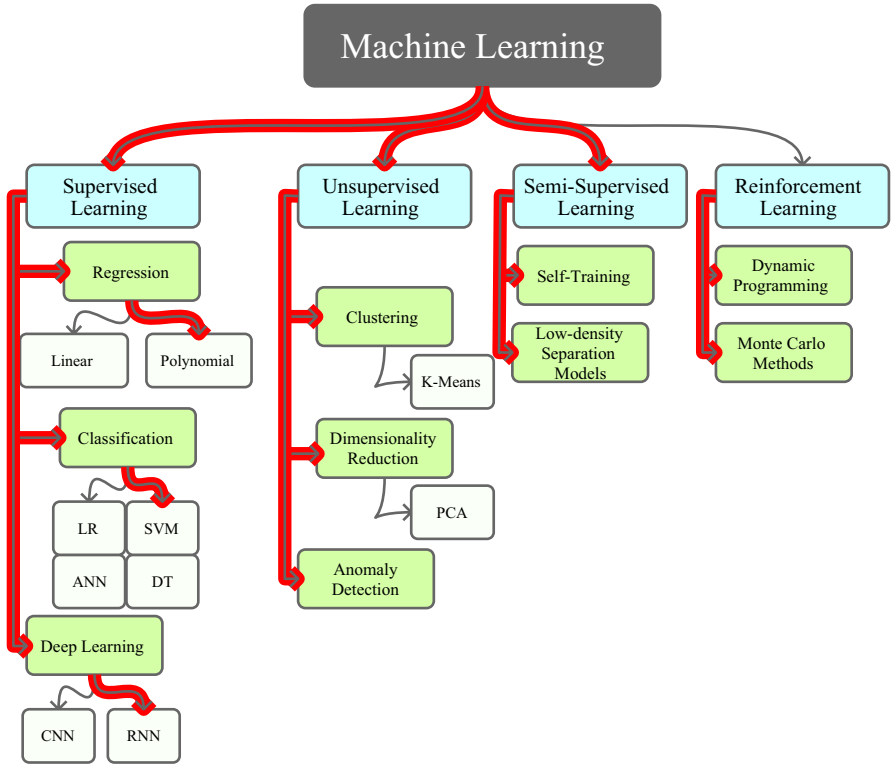



**Fig. 5** The types of machine learning algorithms

data and classifying it appropriately. It is essential to highlight that unsupervised ML is effective at uncovering hidden patterns because it typically works with unlabeled data (Cihan et al., 2020).

Furthermore, semi-supervised learning can handle systems with unlabeled and labeled input and helps overcome the problems with supervised learning. Data labeling for supervised learning is frequently tricky as well as takes time (Guan et al., 2022). Agents are a type of learning system used in reinforcement learning. Through actions that might result in either reward or punishment, the agent gets a greater understanding of its environment. Taoufik et al., (2022) contend that in the absence of human intervention, the agent employs its comprehensive understanding of the surrounding environment to formulate decisions geared toward optimizing profits while minimizing penalties. The current spotlight on deep learning underscores its innovative and promising role in constructing sophisticated prediction models.

Likewise, deep learning has effectively solved many issues (Cihan, 2020; Emmert-Streib et al., 2020). DL is a subclass of ML with more depth for feature extraction. Achieves excellent results in random settings by focusing on extracting features rather than clear training to produce the best results. Also, sufficient training data and critical information power the efficiency of DL models (Mahmoud et al., 2022). Moreover, as the data increases, the performance of DL algorithms increases compared to the traditional ML algorithms despite the increase in data in which the version becomes saturated almost after a period (Pu et al., 2019). The main distinction between both ML and DL is feature extraction. In the field of ML, the process of "feature extraction" is typically performed manually. However, in the DL, feature extraction occurs automatically as part of the learning process. The human process of feature extraction is known to be time-consuming and requires significant labor. Therefore, the implementation of deep learning (DL) techniques has greatly alleviated this burden by automating the feature extraction phase (Taye, 2023). In contrast, ML employs human-crafted engineering features and other feature extraction procedures before using the models. Otherwise, an important advantage for DL over ML methods is that parts are learned and represented automatically (Alom et al., 2019).

The most popular machine learning algorithms used in gasification research

The most commonly used ML algorithms in gasification are artificial neural networks (ANNs), support vector machines (SVM), decision trees (DT), and random forests (RF) (Ascher et al., 2022a; Umenweke et al., 2022).

*Artificial neural networks (ANNs)*

ANN models represent the maximum simplification of human brain networks; this model is often nonlinear, non-limited, incredibly adaptable, and flexible. The three main layers that make up an ANN model are an input layer, one or more hidden layers, and an output layer, as seen in Fig. 6A. As the most popular ML model, ANNs effectively solve many complex non-linear environmental challenges. They have a long history of success in thermal management, landfill, anaerobic digestion, composting, and MSW treatment. ANNs typically have superior predictive performance and calculation efficiency than other algorithms, especially when processing large amounts of data (H. nan Guo et al., 2021). The probability that nonlinear and random data will be effectively represented increases with the amount of state data the ANN model can obtain (Sedej et al., 2022).

*Support vector machine (SVM)*

In addition to being extensively used for binary classification issues, SVMs are a technique that is also successful when applied to other classification and regression tasks (Fig. 6B). The soft-margin approach can use in cases where data cannot be separated linearly, for example, by utilizing the hinge loss function. The SVMs approach could be extended to non-linear problems by using kernel functions. A collection of mathematical operations known as kernel functions transform the input into the required format (Ascher et al., 2022b; Hastie et al., 2009). According to experimental evidence, SVMs appear to work effectively for a variety of applications in the real world. They have been shown to achieve great results for limited data sets in terms of prediction accuracy. SVMs are an excellent choice, specifically for data sets with high-dimensional (Ascher et al., 2022a, b). SVMs also have the benefit of having low sensitivity to outliers. Lastly, a successful model requires the proper kernel function to be chosen (Hastie et al., 2009).

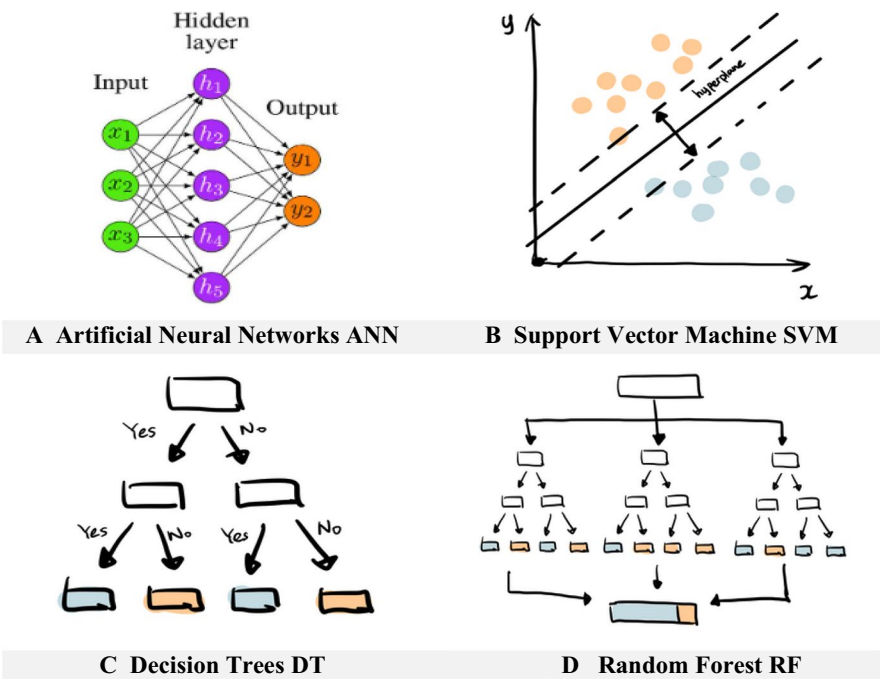



**Fig. 6** Schematic of relevant machine learning methods (Emmert-Streib et al., 2020; Towards Data Science 2020, Accessed: 28.01.2023)

*Decision trees (DT) and random forests (RF)*

The DT algorithm is beneficial for decision-making and operations research. The algorithm divides the feature space into various areas while generating a decision tree. Each region has a split point, and each part that results from the dividing goes through the process again. Many algorithms use bagging, boosting, or ensemble approaches to enhance individual decision trees. RF is the name of one such method. An ensemble of decision trees is produced using the RF approach. Furthermore, each tree's training only uses a small portion of the data set. Every tree is trained using data that is selected at random (Ascher et al., 2022a, b; Cihan & Ozger, 2022). By averaging the outcomes of all decision trees, the RF model's final prediction for regression is determined. In Fig. 6C, D, the DT and RF methodology are presented in a simplified manner. Simple decision trees can be trained quickly, but overfitting is problematic.

Additionally, significant variance is caused by the hierarchy of the method. Accordingly, even little modifications to the training set of data might produce a very different tree. To solve this issue, ensemble methods with a large number of trees might be used. RF and gradient boosting are two main ensemble methods. The main difference between these methods is that while gradient boosting employs many weak trees, RF builds many giant trees (Ascher et al., 2022a, b).

The most popular deep learning methods used in gasification research

DL is a branch of ML, but because of its expansion and advancement as well as the various algorithms created based on it, it will be discussed individually in this section. Firstly, DL is a set of algorithms that simulates the human brain's structure in order to resolve complicated tasks (Forootan et al., 2022). A deep learning model with many conversion layers and an activation function is based on logistic regression. Despite having a linear regression foundation, its many neural nodes, also known as neural networks, set it apart from conventional statistical regression (Umenweke et al., 2022). Deep learning is vital for learning complicated nonlinear connections because of its unique ability to generate complex hypotheses automatically. Due to this characteristic, deep learning has solved issues that machine learning models could not solve (Emmert-Streib et al., 2020). There are various deep learning-based models available. The four algorithms we introduce in this section are convolutional neural networks (CNNs), generative adversarial networks

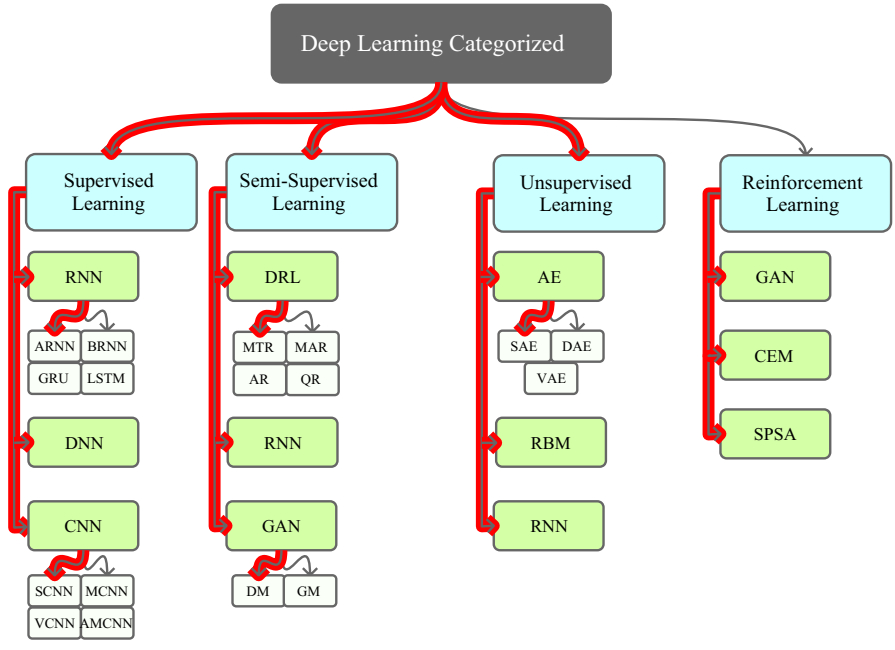



**Fig. 7** Deep learning categorized

(GANs), auto-encoders (AE), and recurrent neural networks (RNNs). The fact that these algorithms are constantly being improved and there is always a need to address new issues and challenges has led to their successful application in several studies.

As in machine learning, supervised, semi-supervised, unsupervised, and reinforcement learning are the four types of deep learning (Fig. 7). Labeled data is used in supervised learning, and the environment comprises a number of inputs and matching outputs. Learning that takes place using partially labeled datasets is called semi-supervised learning. Additionally, methods that can learn without labels on the data are known as unsupervised learning systems. Accordingly, to find unknown relationships or structures inside the incoming data, in this case, the agent learns the internal representation or critical features. Finally, deep reinforcement is utilized in uncertain situations (Alom et al., 2019). Figure 8 shows the deep learning categorized.

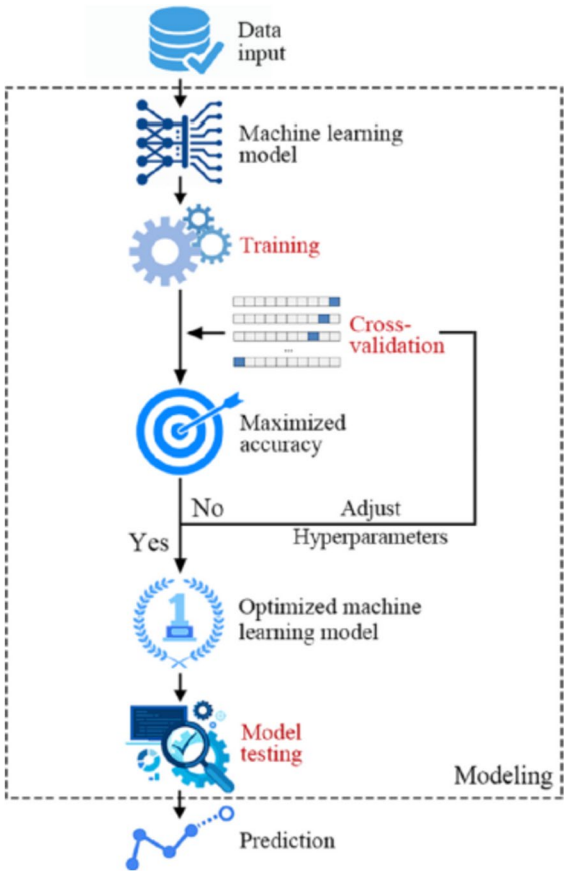



**Fig. 8** Fundamental principle and process of the AI methods (H. nan Guo et al., 2021)

*Convolutional neural networks (CNNs)*

It mainly comprises an output layer, hidden layers, and input layers. The three primary layers in the CNNs model are fully connected, convolutional, and pooling. From an image, the convolutional layers can extract various information (E. Lin et al., 2021). The CNN models are built using convolutional filters that are trained to recognize medical images and extract the relevant information from them (Sarvamangala & Kulkarni, 2022). The year 2012 was a significant turning point for CNN as it began to garner widespread recognition. This surge in popularity can be attributed to the remarkable success of AlexNet, a CNN model that outperformed its counterparts in the imageNet challenge of the same year, achieving unprecedented levels of accuracy and remarkably low error rates (Krizhevsky et al., 2012). One of the most popular deep learning tools now in use is the convolutional neural network (CNN). Face recognition, driverless automobiles, self-service supermarkets, and intelligent medical treatments are just some of the advances made possible by CNN-based computer vision (Z. Li et al., 2022).

Corporate behemoths have used CNN to offer internet services, automatic image tagging, product recommendations, and personalized home feeds (Ranzato et al., 2015). CNN achieved a significant advancement in the field of cancer detection when it was employed by GoogleNet. The utilization of CNN resulted in an accuracy rate of 89% in detecting cancer, surpassing the performance of human pathologists who achieved an accuracy rate of just 70% (Alain et al., 2016).

*Generative adversarial networks (GANs)*

Generative adversarial networks have garnered significant attention and interest among researchers in the field of deep learning since their introduction in 2014 (Goodfellow et al., 2014). A GAN is a type of generative model that comprises a generator and a discriminator, which are commonly implemented as two neural network (NN) models. In recent years, GANs have exhibited their proficiency in generating images and

videos of superior quality, performing style transfer, and accomplishing picture completion tasks (Brophy et al., 2023; Y. Chen et al., 2022).

The utilization of GANs for analyzing time series data is a promising solution to several challenges encountered by existing dataset custodians, which have remained unaddressed by alternative machine learning or regression methodologies (Gui et al., 2023). On the other hand, the scarcity of data is an often-encountered challenge among users, and GANs offer a solution by producing novel data that has not been observed before, thus enhancing limited datasets. In certain instances, data may exhibit missing or damaged elements. GANs have the capability to address this issue by imputing data, wherein they replace the flawed artifacts with information that accurately represents clean data (Brophy et al., 2023). Additionally, the application of deep learning techniques in the field of ophthalmology has witnessed notable progress, resulting in enhanced diagnostic capabilities. The GAN has exhibited exceptional capabilities in the domains of image synthesis and image-to-image translation (You et al., 2022).

*Auto-encoders (AE)*

Another form of neural network is an encoder, specifically designed to acquire reduced-dimensional representations of data with greater dimensions. This facilitates the acquisition of solely the salient components of the higher dimensional picture. The subject matter consists of three integral components. The concepts of encoder, bottleneck, and decoder are fundamental components in various information processing systems. These components play a crucial role in transforming and reconstructing data in a structured manner. The encoder is responsible for converting input (Cihan, 2020; Narayan et al., 2023). AE is optimized for encoding data into a compact and meaningful representation and decoding it back into the original data with high accuracy (Bank et al., 2023). In order to recreate the original input data, AE are models that can perform dimensionality transformations (Aguilar et al., 2023). Autoencoders are typically characterized by their non-linear nature, which arises from the utilization of activation functions inside the neural network framework. The aforementioned constraint restricts the system's capacity to offer interpretability, a highly esteemed characteristic in the field of anomaly identification (Pan et al., 2023).

*Recurrent neural networks (RNNs)*

In the context of neural networks, it is typically assumed that the output and input are completely separate things. However, in certain scenarios, such as predicting the subsequent phrase in a sentence, the network must possess the ability to retain information about the preceding term. The problem at hand is addressed by the utilization of recurrent neural networks (RNNs), which incorporate a hidden layer to resolve it. The concealed layer preserves certain information regarding the preceding sequence. The RNN maintains a memory that retains all the previously acquired information from the network (Cihan, 2023; Narayan et al., 2023; Tran et al., 2021).

The accurate prediction of traffic patterns is crucial for the effective functioning and overall efficacy of intelligent transportation systems. In recent years, RNNs have been widely utilized in traffic forecasting to effectively capture and represent the spatial and temporal connections inherent in the data (W. Jiang & Luo, 2022). According to Tran et al., (2021), RNNs are well-suited for handling time series data due to their ability to capture the temporal dynamics within a sequence. This is achieved through the utilization of feedback connections, which enable the transmission of information from prior inputs to subsequent ones. Nevertheless, a superficial or rudimentary RNN frequently confronts the issue of the vanishing gradient problem.

Consequently, modeling the conversion process can aid in understanding response events and making predictions about the behavior of the conversion system as a whole. Some advantages and disadvantages for various DL and ML modeling methodologies are described in Table 4, respectively. Finally, in these scenarios, modeling is an effective technique for developing a unit based on predictions generated by the model utilizing a variety of operating factors and feedstock. The efficiency of a gasification reactor's responsiveness to changes in various operational and design factors can be assessed using an appropriate model after it has been confirmed. Successful models could allow creators to theorize and expect the effects of variables, which can help create and

**Table 4** Advantages and disadvantages of some M and DL models that are used regularly in gasification studies

| | Models | Advantages | Disadvantages | Reference |
|---|---|---|---|---|
| Machine learning | ANNs | • Any possible interactions between predictor variables can be easily mapped<br>• Modeling complicated non-linear processes<br>• To improve, it demands less training<br>• It is comparatively memory efficient | • The issue of the black box as well as the absence of an explanation<br>• It is prone to overfitting if not carefully monitored | (H. nan Guo et al., 2021) |
| | SVM | • Suitable for tasks involving classification and regression<br>• Great forecast accuracy for small datasets in practical situations<br>• Great opportunity for multidimensional data<br>• Memory-efficient | • When there are more features per data point than training samples, it does not operate well<br>• With larger and noisy datasets, it is inappropriate | (Liao & Yao, 2021) |
| | DT | • Suitable for tasks involving classification and regression<br>• Applying easy<br>• Pre-processing of the dataset is minimal<br>• Enables consumers to determine the relevance of features easily | • Extreme variance results from the hierarchy<br>• The more trees there are also more calculation is needed<br>• lacks smooth in its primary operation<br>• Overfitting | (Umenweke et al., 2022) |
| | RF | • Enhances the decision trees<br>• Overcome decision tree overfitting challenges<br>• Possess fewer hyperparameters and perform well | • The more trees there are also more calculation is needed<br>• Even a tiny change in the data causes the algorithm to change significantly<br>• It is lying to overfitting, and hyperparameter tuning is needed<br>• It is challenging to understand the final model | (Umenweke et al., 2022) |
| Deep learning | CNN | • The utilization of pooling operations enables the reduction of training data dimensions and the establishment of translational invariance to changes and distortions | • The need for storing or processing data has increased<br>• The responses provided are inadequate in terms of their level of detail and lack of clear explanation<br>• Long duration | (Da'u and Salim, 2020) |
| | GAN | • Markov chains are not necessary; backpropagation is all that is required<br>• No requirements for inference<br>• It has the capacity to be united due to the variety of roles<br>• Adversarial networks are capable of representing sharp and degraded distributions | • The computation is time-consuming because it must be performed repeatedly<br>• The training procedure might be difficult<br>• The task of processing lengthy sequences is intricate<br>• The problems of explosion and gradual vanishing | (K. Lin et al., 2022) |

**Table 4** (continued)

| Models | Advantages | Disadvantages | Reference |
|---|---|---|---|
| AE | • It is not necessary to learn dense layers<br>• The autoencoder is more efficient at learning many layers<br>• Suitable for feature dimension reduction and hierarchical feature extraction | • Demand a significant amount of data and computing resources<br>• Instead of concentrating on getting the pertinent information, it extracts all the information<br>• The data provided is quite specific and focused | (Abdel-Jaber et al., 2022) |
| RNN | • Capture temporal dependencies and sequential information<br>• Processing inputs of any length is possible<br>• Avoid the problems of gradient degradation<br>• Helpful in time series forecasting since it stores all past data<br>• As the input size grows, the model size stays the same | • RNN are simple and powerful, but they are difficult to train<br>• The vanishing gradient and exploding gradient difficulties make this model unmanageable<br>• Tanh and relu activation functions prevent it from processing extended sequences | (Abdel-Nasser Sharkawy, 2020) |

apply this technology without further experimental observations.

## The general strategy of selection ML and DL algorithms

The distinction between deep learning and machine learning lies in the divergent learning mechanisms employed by each algorithm. Deep learning has the capability to utilize labeled datasets, commonly referred to as supervised learning, in order to enhance its algorithmic performance. However, it is important to note that deep learning is not inherently reliant on the availability of labeled datasets for its operation (Taye, 2023). Deep learning has the capability to process unstructured data in its original state, such as text or images, and it possesses the ability to autonomously identify the specific properties that differentiate various categories of data from each other (Ahmed et al., 2023). However, machine learning relies more heavily on human intervention in the learning process. The identification of features that facilitate the differentiation of data inputs is typically carried out by human experts, who often rely on structured data for effective learning (Janiesch et al., 2021).

When discussing the process of model selection, it is imperative to move beyond the notion of a one "best" model. Predictive error is an inherent characteristic of all models, owing to the presence of statistical noise in the data, the incompleteness of the data sample, and the inherent limits associated with each distinct model type. The ability to be maintained and low model complexity may be two such requirements that may be imposed by the project's stakeholders. Therefore, a less skilled but more straightforward model could be more appealing (Raschka, 2020).

## Artificial intelligence process

In recent years, sectors relating to the environment, such as treating solid waste, wastewater, and air pollution, have increasingly benefited from using AI. This system is capable of independently acquiring and integrating information. Using relationships in the experimental result to make wise decisions in new situations will help simplify the linkages among intake as well as outcomes. Figure 8 illustrates the basic procedure for AI (H. nan Guo et al., 2021).

The three steps of a standard AI process are training, cross-validation, and testing. Training Step: The ML model is trained by adjusting various model parameters using the training dataset (not hyper parameters). Cross-validation step: The best model is chosen using a validation dataset by setting the model hyperparameters. Testing step: The chosen model's performance is further assessed on

a test dataset. The model is then prepared for forecasting (H. nan Guo et al., 2021).

Data validation and model evaluation strategies

*Data validation*

It is a process used to enhance the quality and reliability of the dataset. The objective of data validation is to enhance the accuracy and usability of a dataset by identifying and addressing defects, anomalies, and errors in the data content. During this phase, many procedures are undertaken, including data cleansing, addressing missing data, managing outliers, and verifying data type compatibility. Data validation is an essential and foundational process within the realm of data analysis and AI research, as the efficacy of models is heavily influenced by the quality of the underlying data (AkyolK & Karaci, 2021).

*Cross-validation*

Cross-validation is a widely employed approach utilized for the assessment of an AI model's performance. The generalization ability of the model is assessed by partitioning the dataset into separate subsets for training and testing purposes. The objective is to assess the model's ability to generalize well in the presence of challenges such as overfitting or underfitting (Cihan et al., 2021b). Cross-validation methods encompass several strategies, including K-fold cross-validation, stratified cross-validation, leave-one-out, and nested cross-validation, as indicated in Table 5, which are employed for the purpose of hyperparameter tuning.

*Testing*

Testing is a procedural method employed to assess the efficacy of an artificial intelligence model in relation to its performance on authentic, real-world datasets. During this phase, once the model has been trained on the provided data, its predictive accuracy and generalization capability are assessed by employing a separate test dataset (Swiecki et al., 2022). The process of testing enables us to gain insights into the functioning of the model within real-world scenarios, while also assessing the level of dependability exhibited by said model. The evaluation of model performance in this procedure involves the utilization of metrics like as accuracy, precision, and recall, which are assessed using independent test data. Additionally, a crucial aspect of this phase is evaluating the model's interpretability and making necessary adjustments or enhancements (Ali et al., 2023).

Model performance evaluation criteria

Sensitivity analysis is used to determine if artificial intelligence models can accurately anticipate future

**Table 5** Types of cross-validation strategies

| Technical | Definition |
|---|---|
| K-fold cross-validation | The dataset is partitioned into "k" folds in a random manner. The model undergoes k iterations of training and testing. The test data consists of one piece at a time, whereas the training data comprises the remaining pieces. The method of total performance evaluation is widely used and has proven to be successful |
| Stratified cross-validation | The dataset has been stratified in a manner that ensures the class distribution of each floor accurately represents the class distribution of the original dataset. This ensures that each floor is representative. It is suitable for datasets with unbalanced classes |
| Leave-one-out cross-validation | In this approach, every individual data point is utilized as a test set in a sequential manner, while the remaining data points are employed as training data. This approach involves utilizing a significant portion of the available data |
| Group cross-validation | The utilization of a dataset occurs when samples are partitioned into distinct groups. This particular approach is particularly advantageous in terms of preserving autonomy and minimizing interdependence among various groupings |
| Nested cross-validation | This method is employed for the purpose of hyperparameter adjustment and model selection. The methodology comprises of an inner cross-validation loop and an outside cross-validation loop. The utilization of cross-validation techniques mitigates the likelihood of overfitting hyperparameters and enhances the assessment of model performance |

events depending on the dataset's characteristics (Cihan, 2022). Absolute error (AE), coefficient of determination ($R^2$), adjusted coefficient of determination (Adj $R^2$), mean absolute deviation (MAD), mean absolute error (MAE), mean absolute percentage error (MAPE), mean error (ME), mean squared error (MSE), root means squared error (RMSE), normalized root mean squared error (NRMSE), relative absolute error (RAE), relative percentage error (RPE), standard deviation (SD), and standard error (SE) are calculated in order to compare the AI models (Afolabi et al., 2020; Cihan et al., 2019, 2021a; Cihan, 2022a; Fang et al., 2022). These criteria are used to determine the precision and dependability of the AI models. Table 6 describes a brief of AI model estimate metrics (Afolabi et al., 2020; Aghbashlo et al., 2021; Umenweke et al., 2022).

## Application of AI to simulate gasification processes

The gasification process is extremely complicated as it using accurate algorithms is necessary. Several articles have reported on using AI to model the biomass gasification process. The primary objective of gasification modeling is to maximize process effectiveness and productivity based on syngas output and $H_2$ yield in addition to gasification productivity. Table 7 provides a brief of the AI algorithms employed in biomass gasification. We only took into consideration publications published in 2020 or after. Figure 9 illustrates the substantial rise in papers that use ML, DL, and AI techniques to simulate gasification. Data were obtained from the "Web of Science" website using the keywords "machine learning" + "gasification," "deep learning" + "gasification," and "artificial intelligence" + "gasification."

### The common AI models utilized for modeling gasification

As seen in the figure, while machine learning plays a prominent role in gasification studies, deep learning plays a minor role, and this is because deep learning has been used in gasification applications newly. ANNs have been the most frequently employed AI method for modeling the gasification process. Overall, models produced satisfactory prediction results. $R^2$ values near one and typically over 0.9 show the ANNs' great prediction accuracy. A number of research have provided ML-based simulations of the gasification process. The literature research revealed that the most widely used ML models for gasification processes were ANN, SVM, RF, DT, and GBR. In contrast, the most widely used DL models in gasification have been particle swarm optimization (PSO), backpropagation (BP), and multilayer realization (MLP).

### The major gasification AI uses

Based on the literature examined, there have been several uses of AI models in simulating gasification variables. Among the often-studied target variables were syngas yields, syngas composition (CO, $CO_2$, $CH_4$, $H_2$), $H_2$ yield, LHV, and higher heating value (HHV) of gasification products. Most research has used biomass characteristics (proximate and ultimate analysis) and gasification conditions (temperature, Steam/carbon ratio, reaction time, and feed particle size) as input for AI models. Because of their capacity to recognize highly non-linear relationships between inputs and outputs, ANNs are particularly suited for modeling gasification. For instance, models based on ANNs were employed to forecast $H_2$ yield (Bahadar et al., 2022; Haq et al., 2022; Jamro et al., 2023; Kumar Sharma et al., 2022; Li et al., 2021a; Li & Song, 2022; Safarian et al., 2021), gasification behavior and syngas characteristics (Özveren et al., 2022), syngas compositions and LHV (Hashem Samadi et al., 2023; Kargbo et al., 2021; Kim et al., 2023), efficiency of carbon conversion (Li & Song, 2022), syngas yield (Kargbo et al., 2021; Li et al., 2021c; Liu et al., 2022; Sun et al., 2022; Zhang et al., 2022), and chemical exergy of syngas (Sezer et al., 2021).

Finally, the number of papers published on the use of AI techniques in the gasification of biomass is indicated in Fig. 10 based on the studies examined in Table 7 and taken as a whole. Most publications (34%) were ANN-based studies, followed by SVM, RF, GBR, and Gaussian process regression (GPR), whereas the other studies on gasification focused on other AI techniques (DT, PSO, SVR, etc.).

Following a survey of studies on gasification, we find that there has been less innovation because the seven most well-known ML techniques have been

**Table 6** The statistical criteria applied in AI models

| Statistical criteria | Formula | Description |
|---|---|---|
| AE | $AE = \lvert \text{actual values} - \text{predicted values} \rvert$ | Demonstrates pure contrast among the expected and produced results. A negative result is not taken into consideration |
| $R^2$ | $R^2 = 1 - (\text{sums of squares error/ sums of squares total})$ | When forecasting the result of a certain event, it investigates how variations in one variable can be accounted for by variations in a second variable. Higher prediction accuracy is indicated by a value nearer to 1 |
| Adj $R^2$ | $\text{Adj } R^2 = 1 - ((1 - R^2) \times \frac{n-1}{n-k-1})$ | Used to calculate the model's fit by figuring out how much one parameter varies from another. Higher prediction accuracy is indicated by a value nearer to 1 |
| MAD | $\text{MAD} = \frac{1}{n} \sum_{i-1}^{n} \lvert \text{actual output} - \text{mean actual output} \rvert$ | The typical distance between an observed value and the mean is displayed. This provides insight into the extent of variation within a given dataset |
| MAE | $\text{MAE} = \frac{1}{n} \sum_{i-1}^{n} \lvert \text{actual values} - \text{predicted values} \rvert$ | Is the average size of predictions' errors without considering their direction. Less suitable for models with significant errors and not sensitive to outliers. A smaller value meant improved prediction results |
| MAPE | $\text{MAPE} = \frac{1}{n} \sum_{i-1}^{n} \lvert \frac{\text{actual values} - \text{predicted value}}{\text{actual value}} \rvert \times 100$ | Determines a model's % accuracy. Works effectively, assuming there are no extremes or zeros in the data |
| ME | $\text{ME} = \frac{1}{n} \sum_{i-1}^{n} \lvert \text{actual value} - \text{predicted value} \rvert$ | A proportion among all outcomes to discrepancies between output projections and actual output |
| MSE | $\text{MSE} = \frac{1}{n} \sum_{i-1}^{n} \lvert \text{actual value} - \text{predicted values} \rvert^2$ | When the data includes unforeseen or outlier values, it is helpful. A smaller value meant improved prediction results |
| RMSE | $\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i-1}^{n} \lvert \text{actual value} - \text{predicted values} \rvert^2}$ | Functional systems have substantial flaws which might negatively affect how well they operate. A smaller value meant improved prediction results |
| NRMSE | $\text{NRMSE} = \frac{RMSE}{\text{average of observation values}}$ | They are frequently used to compare models with different scales |
| RAE | $\text{RAE} = \frac{\sum_{i-1}^{n} \lvert (\text{predicted value} - \text{actual values})^2 \rvert^{1/2}}{\sum_{i-1}^{n} \lvert \text{actual values}^2 \rvert^{1/2}}$ | It shows the proportion between the residual values and the model-derived error |
| RPE | $\text{RPE} = \frac{\text{mean absolute error}}{\text{mean value of observation}} \times 100$ | The mean absolute error ratio to the variable's mean value is the percentage |
| SD | $\text{SD} = \sqrt{\frac{\sum (\text{Actual} - \text{mean})^2}{n}}$ | Explains the flexibility of the dataset relating to the average. The estimated value is near the dataset's mean if the SD value is near zero |
| SE | $\text{SE} = \frac{SD}{\sqrt{n}}$ | The accuracy of the estimated sample mean is evaluated using SE. The rising sample size indicates a decrease in SE |

applied in most cases. There are several applications for different AI algorithms that require concentration. Further investigations into several other algorithms, including CNN, LSTM, and RNN, are recommended.

In the study of Kartal and Özveren, (2020), ANN models regularized with Levenberg–Marquardt methods were used as deep learning models in order to forecast LHV in circulating fluidized bed (CFB) gasifier. For 56 biomasses mentioned in the literature, datasets were created using the CFB model. Six input variables were used to train the ANN model to estimate the syngas LHV. The ANN model's performance was good across all datasets because of its low MSE value (18,435.4) and a high coefficient of determination value ($R^2 > 0.99$). Finally, the ANN model can pretty accurately estimate the LHV of new biomasses if it has been trained with a significant number and variety of biomass LHVs.

**Table 7** Recent investigations into the use of AI models for gasification

| Feedstock | Process | AI models | Predicted parameters | Effective model | $R^2$ value | Reference |
|---|---|---|---|---|---|---|
| Municipal solid waste | Biomass gasification | ANN | $H_2$ yield | ANN | 0.939 | (Jamro et al., 2023) |
| Bagasse pellets, wood pellets, and wood chips | Biomass gasification | MLP-NN | Syngas composition, LHV | MLP-NN | 0.952 | (Hashem Samadi et al., 2023) |
| Woody biomass and agricultural residues | Biomass gasification | RF, SVM, ANN | Syngas compositions, LHV | RF | 0.809–0.946 | (Kim et al., 2023) |
| Coal | Biomass gasification | FFBP-ANN, CFBP-ANN, CFBP-GA-ANN | Carbon conversion efficiency, H2 yield | CFBP-GA-ANN | 0.997 | (W. Li & Song, 2022) |
| Coal | HTG | GBR, RF, SVR, DT, ANN, ABR | Syngas yield | GBR | 0.997 | (S. Liu et al., 2022) |
| Coal and sawdust | Co-gasification | SVM, GPR, ANN | $H_2$ yield | ANN | 0.972–0.978 | (Bahadar et al., 2022) |
| Biomass wastes from oil palm | Co-gasification | SVM, GPR, LRQM | $H_2$ yield | LRQM | 0.97 | (Ayodele et al., 2022) |
| Sewage sludge | HTG | SVM, GPR, ET, ANN | $H_2$ yield | GPR | 0.997 | (Haq et al., 2022) |
| Pinewood sawdust | Biomass gasification | PSO-ANN | Bio-oil, biochar, and syngas yield | PSO-ANN | 0.985 | (Sun et al., 2022) |
| Yimin lignite (coal) | HTG | BP-NN | Syngas yield | BP-NN | 0.992 | (B. Zhang et al., 2022) |
| Wood chips | Biomass gasification | LSTM-RNN | Spatio-temporal temperature | LSTM-RNN | MAE < 6 | (Khurram Faridi et al., 2022) |
| Cellulose, hemicellulose, lignin | Biomass gasification | GRU-RNN | The reactant and product compositions | GRU-RNN | $R^2$ 0.999 | (K. G. Sharma et al., 2022) |
| Biomass and waste | Biomass gasification | RF, GBR, XGB, Ada Boost, SVM, ANN, SL | Model the gasification | GBR | 0.90 | (Ascher et al., 2022a) |
| Municipal solid waste | Biomass gasification | OEM | Syngas yield, LHV, LHVp | OEM | 0.99 | (Kardani et al., 2021) |
| Animal manure, sewage sludge, and food waste | HTG | GBR | $H_2$ yield | GBR | 0.90 | (Li et al., 2021b) |
| Sewage wastes, forest residues, and corps | Biomass gasification | ANN | Chemical exergy of syngas | ANN | 0.999 | (Sezer et al., 2021) |
| Agricultural and herbaceous wastes | Biomass gasification | ANN | Syngas exergy value and $H_2$ yield | ANN | 0.99 | (Sezer & Özveren, 2021) |
| Waste wood | Two-stage gasification | ANN | syngas yield, Composition | ANN | 0.99 | (Kargbo et al., 2021) |
| Municipal solid waste and agricultural waste | HTG | GPR, ANN, SVM, RF | $H_2$ yield | RF | 0.978 | (Zhao et al., 2021) |

**Table 7** (continued)

| Feedstock | Process | AI models | Predicted parameters | Effective model | $R^2$ value | Reference |
|---|---|---|---|---|---|---|
| Sludge, food waste, and manure | HTG | Developed NN | $H_2$ Yield | ANN | 0.85 | (Li et al., 2021a) |
| Woody, herbaceous, and agricultural biomasses | Biomass gasification | ANN | $H_2$ yield | ANN | 0.999 | (Safarian et al., 2021) |
| Plastic and rubber wastes | Co-gasification | RBF-ANN, MLP-ANN | $H_2$ Yield | MLP-ANN | 0.990 | (Ayodele et al., 2021) |
| Woody, herbaceous, agricultural, animal, mixed, and contaminated biomasses | Biomass gasification | ANN with thermodynamic equilibrium | Net output power | Developed ANN | 0.99 | (Safarian et al., 2020) |
| Pinecone and wood pellet | Biomass gasification | PR, SVM, DTR, MLP | Syngas Composition, HHV | MLP, DTR | 0.92–0.94 | (Elmaz et al., 2020) |
| Food waste, manure, and sludge | HTG | GBR | Syngas Composition | GBR | 0.90–0.95 | (Li et al., 2020) |
| Different biomasses | Biomass gasification | LM-ANN | syngas composition, LHV | LM-ANN | 0.999 | (Kartal & Özveren, 2020) |

This study predicted the composition of syngas (CO, $CO_2$, $H_2$, and $CH_4$) produced by the conversion of HTG waste using a GBR model with appropriate hyper-parameters. From analyzed studies on HTG of sludge, food waste, and manure, 295 pieces of data were gathered. The testing $R^2$ was 0.92, 0.90, 0.95, and 0.92 for predicting the composition of $H_2$, $CH_4$, $CO_2$, and CO in syngas. In addition to providing a solid framework for creating ML-based process optimization or inverse design for trials, the established model offered helpful inference to establish the relationship between the inputs and outcomes. Additionally, the creation of an ML model for predicting the syngas composition (J. Li et al., 2020).

Elmaz et al., (2020) used a set of experimentally gathered data to estimate the CO, $CO_2$, $CH_4$, $H_2$, and HHV outputs of the downdraft biomass gasification process using polynomial regression (PR), support vector regression (SVR), decision tree regression (DTR), and multilayer perceptron (MLP) approaches. The obtained results demonstrate that MLP and DTR outperformed the other methods significantly by reaching $R^2 > 0.92$ for $CH_4$, $H_2$, and HHV outputs and $R^2 > 0.85$ for CO and $CO_2$ outputs. One approach cannot be utilized for all of the outputs of biomass gasification due to the various complexity levels of those products. On the other hand, out of all the suggested approaches, PR achieved the worst. When predicting CO and $CO_2$ relative to different outputs, the performance of all approaches declined; as a result, there is potential for improvement for both hyper-parameter and feature selection to boost forecasting accuracy for these outputs.

In another study, for the downdraft biomass gasification integrated power generation unit, an ANN model combined with a thermodynamic equilibrium technique is developed to forecast the net output power. With $R^2 > 0.999$, the created ANN model demonstrated great prediction accuracy. The compositions utilized for proximate analysis (M, VM, FC, and A) indicated between 7 and 11% of the influence on the output power, while the parameters taken into account for biomass composition (C, H, O, S, and N) represented between 8 and 12%. Additionally, the gasifier temperature considerably impacts output power prediction, with a 13 percent impact. The reduction zone temperature is the most efficient variable for producing $H_2$ and CO, which improves syngas's LHV. The study found that a system's power output

is maximized when the C/H ratio is between 2.08 and 2.5 and the C/O ratio is between 5 and 7. The findings demonstrate that rising temperatures, which increase syngas LHV, promote the production of $H_2$ and CO. Hence, the system's output power is improved. Furthermore, it shows that the model applies to a wide range of feedstocks. Also, the model may be helpful for selecting appropriate biomass feedstocks for integrated power plants that use gasification technology to extract energy (Safarian et al., 2020).

In a different study, waste plastic and rubber co-gasification to produce hydrogen was modeled using feedforward radial basis function (RBF) and MLP-ANN. The maximum amount of hydrogen was created when the particle size was 0.57 mm, and the temperature was 550 °C. All of the input parameters considerably impacted the model output, and the 1-layer MLP with $R^2 > 0.990$ had the best performance. As a result, in the case of making a significant decision in the co-gasification process for hydrogen production, the 1-LMLP algorithm, as well as the level of importance analysis, could be used to identify the parameters that might affect hydrogen production when considering a variety of feedstocks (Ayodele et al., 2021).

Safarian et al., (2021) also utilized some other ML methods for biomass gasification. An ANN-based strategy was developed to precisely forecast the performance of downdraft biomass gasification to produce $H_2$. One thousand eight hundred samples from the simulation of 50 distinct feedstocks under various operating circumstances were used to train the proposed ANN model. With $R^2 > 0.999$ and RMSE 0.25, the output and input data were in good agreement. An extensive range of biomasses can be used with the ANN-based model. Moreover, the findings indicate the proportional influence of different biomass characteristics and system operating parameters on the output of biohydrogen. The temperature range between 900 and 1100 °C was ideal for producing

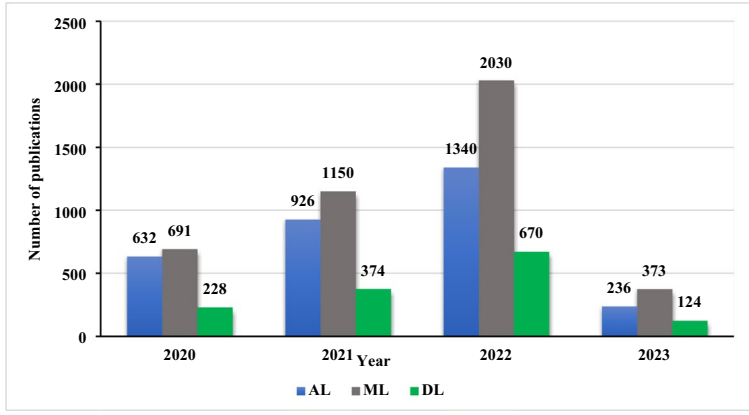



**Fig. 9** Prevalence of AI, ML, and DL use for gasification modeling applications

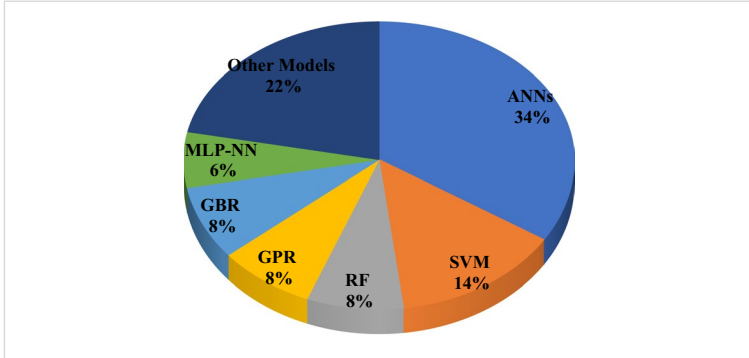



**Fig. 10** Distribution of AI techniques by the percentage used in studies

more biohydrogen. Additionally, based on a gasification system connected to a W-G shift and a hydrogen recovery unit, this model can be used experimentally to screen appropriate biomasses for hydrogen extraction.

Since it takes time and money to produce $H_2$ gas from wet organic waste using supercritical water gasification, Li et al. (2021a) created a standardized machine learning model to forecast synthesis gas content from SCWG processes, which include both catalytic and non-catalytic systems. Seven hundred eighteen data points were obtained from the 46 publications. The created NN model demonstrated prediction accuracy for all systems assessed with $R^2 > 0.85$. As determined by the results, the higher $H_2$ yield in all SCWG systems was caused by a lower solid concentration and higher temperature. When the temperature was raised from 400 to 440 °C, the $H_2$ output rose by a factor of 1.44. The created model assisted in selecting catalysts and offered the ideal circumstances for increasing the production of $H_2$-rich syngas. It also emphasized that, given the perfect operating conditions, Fe-based catalysts had a more remarkable ability to improve the SCWG of wet wastes. Additionally, SCWG temperature and solid feedstock concentration were the main factors affecting syngas composition.

Another research investigated the $H_2$ yield. The performance of four machine learning algorithms (ANN, GPR, SVM, and RF) to forecast $H_2$ yield during HTG was tested. The models were also used to investigate how the biomass's C, H, and O contents affected the exergy efficiency. According to the RF model, the highest hydrogen reactions performance (45.6%) and exergy efficiency (43.3%) were produced by feedstock biomass with a large O concentration and a low H/C ratio. Similarly, 700 °C was the processing temp that improved $H_2$ yield. The findings indicated that the RF model performed better than every other model in forecasting $H_2$ creation ($R^2 = 0.9782$). Finally, the proposed ML models might be used for future planning and improvement of the HTG process (Zhao et al., 2021).

In an earlier study, ANN was developed using experimental data to predict the yield and composition of syngas (tar, residue, $H_2$, CO, and $CO_2$ $CH_4$) more accurately during two-stage gasification. The ANN model's output and the experimental data showed excellent agreement ($R^2 > 0.99$). Therefore, the proposed ANNs models may be applied for process management and optimization in a two-stage biomass gasification system. The result showed that at pyrolysis temp of 900 °C (1st stage) and gasification temp of 1000 °C (2nd stage) with a steam/biomass ratio of 3.8, optimum conditions for hydrogen production (70 mol%) and gas production (96.2 wt%) with low $CO_2$ production (16.4 mol%) were found (Kargbo et al., 2021).

According to the authors Sezer and Özveren, (2021),the exergy value of syngas produced by a bubbling fluidized bed gasifier could be predicted by an ANN model ($R^2 > 0.99$). The $H_2$ Concentration in syngas increased between 700 and 850 °C for each biomass sample, and this increase in gasification temperature had a favorable effect. The Aspen Plus® software was used to train the ANN model in their studies, and experimental data from the literature was used to validate it.

Sezer et al., (2021) demonstrated the effectiveness of the developed ANN model in representing complex nonlinear systems. With the support of Bayesian regularized ANN, 32,025 different experimental conditions produced by Aspen Plus® were employed in their study to forecast the chemical exergy of syngas from the downdraft gasifier. The study showed that while the temperature was between 873.15 K and 1000 K, the $H_2$ concentration increased rapidly from 47.00 to 50.35%. After 1000 K, the concentration of $H_2$ slowed down and reached 51.5% at 1180 K. In addition, the LHV reduced from 15,115 kJ/kg to 15,086 kJ/kg as the temperature increased from 873.15 to 930 K. The determined $R^2$ values for the training, test, and hazelnut shell gasification data were 0.9992, 0.9991, and 0.9942, respectively. Additionally, the findings for RMSE for the developed ANN model were within acceptable limits. These findings demonstrate that the ANN model is flexible enough to accurately forecast chemical exergy values of syngas for downdraft gasifiers without the need for complicated computations or expensive experimental experiments.

In order to address the "black-box problem" of machine learning, Li et al. (2021b) developed a new hybrid data-driven and mechanistic modeling method for HTG of wet waste. An integrated GBR optimization model was developed to forecast and enhance the yield of syngas from wet waste HTG. According to the results, the GBR model performed

well regarding prediction, with test $R^2 > 0.90$. The GBR-PSO forecast and the Aspen simulation were utilized to validate gas fraction values. Regarding the outcomes, the GBR-PSO model forecasted that the $H_2$ yield would rise from 13 to 35 mol/kg. The Aspen simulation produced nearly identical findings, with the $H_2$ yield growing from 16 to 35 mol/kg over a temperature rise of 600 to 800 °C. The values and trends of the forecast gas fractions using GBR-PSO and the Aspen simulation are very similar. Additionally, the analysis revealed that the reaction temperature and solid feedstock content were the two significant factors for achieving high $H_2$ production in syngas. The findings indicated that more $H_2$ could be produced by raising the process temperature from 400 to 800 °C and lowering the biomass's solid, carbon, and nitrogen content. In light of this, mechanistic and data-driven modeling can support waste-to-energy conversion.

The simulation and modeling of the municipal solid waste (MSW) gasification process are complicated and computationally expensive because of the porous nature of MSW and the nonlinear relationships among different factors. In this regard, in order to model the MSW gasification in a fluidized bed gasifier, an optimized ensemble model (OEM) based on five advanced as DT, XGB, RF, MLP, and SVR models was established, was established. The five models were improved using the PSO technique. The findings indicated that temperature is the most crucial factor affecting LHV, LHVp, and gas yield. Using the training dataset for LHV prediction, the PSO-DT, PSO-MLP, PSO-RF, PSO-SVR, PSO-XGR, and OEM models achieved $R^2$ values of 0.994, 0.924, 0.985, 0.871, 0.995, and 0.998 respectively. The six models also succeeded in predicting gas yield with $R^2$ values of 0.981, 0.992, 0.987, 0.979, 0.996, and 0.99. In the LHVp prediction, $R^2$ values of 0.972, 0.977, 0.987, 0.945, 0.997, and 0.994 were also attained. According to the simulation results, the suggested OEM performs better than the others in the forecasts of LHV and LHVp, also, the results indicate that it is a promising option for simulating complicated nonlinear thermochemical operations. While PSO-XGB performs better than the OEM in estimating gas yield, demonstrating the viability of using individual OML models to affect complicated thermochemical operations (Kardani et al., 2021).

In a recent study, the gasification of waste and biomass was modeled using seven different machine learning (ML) methods: RF, GBR, XG Boost, Ada Boost, SVM, ANN, and SL. The results show that GBR performs better than the other models, with an $R^2$ of 0.90. The size of the feedstock's particles and the type of gasifying agent used had the biggest effects on the tested models. According to the findings, when the temperature was raised to 1000 °C, the model's forecast syngas production increased from 1.63 to 2.21 $Nm^3$/kg wb. The model's forecast increased due to MSW's high carbon feedstock percentage, and smaller particle size can raise the projected LHV. However, the forecast LHV was down than estimated due to increased particle size and feedstock ash concentration. The results showed that the gasifier's absence of oxygen negatively affected the LHV of the syngas. Interestingly, the comprehension of black box models has increased by integrating local and global prediction algorithms (Ascher et al., 2022a).

For multi-step temperature prediction in a pilot-scale fluidized bed biomass gasifier (FBG), another study suggested a dynamic RNN model based on LSTM. This model predicts the temperature distribution in FBG regarding time and space. According to the validation results, the suggested LSTM-based RNN model could predict the temperature of all the FBG zones one minute in advance with high accuracy (MAE 6). The MAE values for temperature prediction were found to be $< 6$. The MSE values ($< 21$) also showed agreement between the freeboard experimental data and the predicted outlet gas temperature. However, the MSE's predictive value for fluidized bed temperature was relatively more significant (MSE = 103.8). It is due to the fact that the LSTM model performs poorly when the temperature decreases quickly to 250 °C. This happens because the LSTM model was not trained to forecast such a wide range of temperatures. Finally, the LSTM algorithm could be extended to enhance process control techniques (Khurram Faridi et al., 2022).

In this study, an RNN model has been developed to forecast the content of the reactant and the output during biomass gasification in fluidized bed reactors. Three major GRU-based RNN model had been utilized to validate accurate forecasts. The $R^2$ value for each model has been greater than 0.99, showing that even the simplest RNN model can accurately depict

the temporal evolution of species. Additionally, the RNN model has been shown to be proper for avoiding the problem of computationally complex and expensive operations. Likewise, the developed GRU-based RNN model could forecast the temporal evolution of reactant and output (K. G. Sharma et al., 2022).

To improve production efficiency and provide accurate predictions of the gas products for the future coal gasification industry. In B. Zhang et al. (2022) study, using the SCWG experiment of Yimin lignite, the BP-NN, the number of hidden layers, the linear fit model, and the mean impact value (MIV) had been tested to predict the impacts of concentration, residence time, and temperatures on gasification. For the experiment result, the three key factors influencing lignite's SCWG are temperature, concentration, and residence time. The impact of attention was examined at a temperature of 850 °C and a residence period of 120 s. It is evident that when the temperature increases from 600 to 850 °C, the yield of $H_2$, $CH_4$, and $CO_2$ increases significantly. For example, $H_2$ increased from 1.83 to 18.90 mol/kg, a ninefold increase, while $CH_4$ increased from 1.76 to 7.12 mol/kg, a threefold increase. The rapid rise in $H_2$ and $CH_4$ suggests that water vapor has significantly started participating. According to the findings, the single-layer neural network is more fitting than the two-layer neural network. Compared to the linear regression, the ANN model performs significantly better with an $R^2$ of 0.9921 and an RMSE of 0.2952. Moreover, the most crucial variable is temperature.

In another study, the gasification of pinewood particles had been studied using a standard fluidized bed reactor. Researchers tested upon how temperature, equivalence ratio (ER), and steam/biomass ratio (S/B) affected output productivity. The ANN and the PSO-ANN algorithms were developed to forecast the production yield throughout biomass gasification. ER with values between 0.2 and 0.4 and S/B ratio with values between 0.5 and 1.5 had been used. The temperature of the gasification process had been controlled at around 700–900 °C. The gasification of pinewood resulted in the production of syngas and biochar. As the temperature increases, the production of biochar decreases while the yield of syngas increases. A higher temperature enhanced the $H_2O$/$CO_2$ and biochar reaction, which increased the $H_2$ and CO production. According to the results, when compared to the concentrations at 700 and 900 °C, $H_2$ concentrations rose from 15.32 to 19.37% and CO concentration rose from 14.12 to 19.24%. Regression coefficients had been 0.98534, 0.96663, and 0.97312 for training, validation, and test, respectively. The results indicate that the BP-ANN model and the simulation parameters selected were acceptable in this study. According to experimental findings, a higher temperature increased syngas yield while decreasing biochar yield. The findings of the PSO-ANN model indicate the PSO algorithm can be utilized to adjust the weighting of the ANN model and considerably improve predictive performance. Thus, the results show that a valuable technique for predicting product distribution during solid waste gasification is the employment of an ANN model (Sun et al., 2022).

So as to forecast, examine, and assess the hydrogen output from the SCWG of sewage sludge, this study is novel because it takes into account four distinct ML approaches (GPR, ANN, SVM, ET) that are integrated with genetic algorithm (GA). The model of GPR suggested that the Gasification could be made better with high temperatures, as the percentage of hydrogen production increased as the temperature rises from 350 °C up to 760 °C. According to the GPR model, increasing the temperature will enhance gasification. As a result, applying high temperatures improved the success rate of the gasification process. The leading causes of the hydrogen yield were the kinematics of the water–gas shift and steam reforming, which were more effective by extreme temperatures. According to the findings, hydrogen yield was optimum when under pressure (30–32 MPa). Also, the results showed, $H_2$ was found to be rising with growth in moisture content. Due to the gas–water interaction, increasing time only temporarily increased $H_2$ production. However, the production decreases with time due to the methanation reaction. The outcomes suggested that GPR is favored for $R^2 = 0.997$, RMSE = 0.093, and is strongly advised for handling complex variable-target correlation for predicting hydrogen yield. Yet, SVM's effectiveness was subpar; the $R^2$ and RMSE for the ensembled tree (ET) were 0.994, 0.560, and for ANN, they were 0.943, 1.521, respectively. Thus, it will be advantageous to forecast the $H_2$ yield for the experimental work using the best ML approach combined with GA (Haq et al., 2022).

Ayodele et al., (2022) examined the performance of twelve machine learning models built on the

SVM GPR, the non-linear response quadratic model (NLRQM), which uses sequential quadratic programming, and the Levenberg–Marquardt algorithms. SVM regression combined with linear, quadratic, and cubic kernel functions, GPR with rotational, squared, Matern 5/2, and exponential kernel functions, NLRQM employing sequential quadratic programming (SQP), and LM were used to describe the co-gasification process. According to the ML models, the product of syngas was 18.83 vol% with a catalyst loading of 15%, gasification at 700 °C, and a mix ratio of 0.25 of oil palm waste to coconut shells. The highest syngas output, 38.37%, using 30% Portland cement catalyst, was achieved at a gasification temperature of 900 °C with a mixture of coconut shell and oil palm trash that was distributed equally. The $R^2$ values of 0.400, 0.560, and 0.550 obtained using the LSVM, QSVM, and CSVM models, respectively, show that the SVM algorithms did not successfully forecast the observed syngas produced during the experimental testing. As a result, the SVM algorithms were unable to accurately describe the interrelationship among the incoming variables and the targeted production. On the other hand, using GPR algorithms showed enhanced modeling and Syngas production forecast performance. The $R^2$ of 0.85 indicates that as compared to other kernel functions, the GPR included with the Matern 5/2 kernel function offers the best prediction. At the same time, the $R^2$ of 0.710 suggests that the GPR mixed with the exponential kernel function gave a minor performance. Applying linear regression models also demonstrated some promise in estimating the gasification process's syngas output. The performance of the linear regression models was superior to that of the SVM. Nonetheless, as evidenced by the lowest RMSE, MAE, and highest $R^2$, the NLRQM-LM and NLRQM-SQP models performed the best. 0.987 and 0.996 $R^2$ utilizing the NLRQM-LM and NLRQM-SQP, respectively. Based on the sensitivity analysis, the expected composition of syngas is significantly influenced by co-gasification temperature, catalyst loading, blending percentage, and co-gasification temperature.

Another research contrasts prediction accuracy between various ML patterns, including RM, SVM, GPR, and ANN. To overcome the complex reactions in coal and biomass co-gasification, Bahadar et al., (2022) used those models for modeling the production of high-hydrogen syngas through the Co-gasification and gasification of coal and biomass. The performances of the procedures were evaluated using the $R^2$, RMSE, MSE, and MAE. At all times, algorithms used by ANN performed better and provided reliable syngas during co-gasification is expected to be hydrogen-rich. As seen in the results, when the gasification heat and $O_2$ material increase, the anticipated and actual hydrogen production increases. In order to achieve the predicted hydrogen yield of 85%, The ratio of adsorbent to biomass and the gasification temperature were optimized at 680 °C and 1.2, respectively. Thus, the GPR patterns are ineffective in co-gasification simulation for the generation of hydrogen-rich syngas. In contrast, the LM-ANN and BR-ANN models offered accurate forecasts for the hydrogen generated by co-gasification with $R^2$ 0.978 and 0.972, respectively. This study obtained the optimum predicted $H_2$/CO ratio when the temperature was 850 °C, and the equivalency ratio was 0.24.

In this study, the ML with black box mechanism was utilized to forecast the yields of $H_2$, CO, $CH_4$, and $CO_2$. As a data set, 208 SCWG experimental samples of coal were used. Six ML models' prediction and training processes were examined. Among these patterns, the GBR pattern had the best overall results for predicting gas yield, followed by RF, SVR, DT, ANN, and ABR. (AdaBoost regression). As stated by the SHAP (Shapley Additive exPlanations) qualities, the temperature and the residence time had a positive correlation along with the gas flow rate. While concentration's impact on $CH_4$ and CO was minimal, the effect on $CO_2$ and $H_2$ is rather significant and negatively linked. The equivalent oxidant rate barely makes a dent in the gas output for low ER levels. In contrast, the high ER value enhanced the production and use of $CO_2$ and $H_2$. Additionally, to the results, the operational circumstances' share of the gas yield was 88.55%, while the contribution of coal properties to the gas yield was only 11.45%. The six created models' total performance rankings were GBR > RF > SVR > DT > ANN > ABR. The GBR model with $R^2$ 0.997, which performed the best among the six models, was chosen to study how features affect gas yield (S. Liu et al., 2022).

Similarly, Li and Song, (2022) used three different ANN models, including feed-forward back propagation brain connection (FFBP). The fixed-bed catalytic coal gasification process uses the cascade-forward back propagation neural network with Levenberge

Marquardt algorithms (CFBP) and the cascade-forward back propagation neural network with genetic algorithm (CFBP-GA) to forecast the carbon conversion and hydrogen output. According to the results, all three of the established ANN models had $R^2$ values above 0.9, but the CFBP-GA performed better than the other two models with $E^2 = 0.000241$ and $R^2 = 0.9978$. According to a materiality study, the catalyst type, catalyst loading, and temperature had the most incredible effects on carbon conversion and hydrogen yield. Most notably, the simulated carbon conversion increased from 0.33 to 0.93 when the temperature rose from 973 to 1173 K. Also, the carbon conversion varied considerably at the same temperature, ranging from 0.33 to 0.58. These occurred because the endothermic water–gas shift reaction and steam reforming process were encouraged as the temperature rose. Additionally, at a temperature increase from 973 to 1173 K, the simulated hydrogen yield went from 0.53 to 1.24 mol (mol C)$^{-1}$. They were primarily brought on by the acceleration of steam gasification and water–gas shift processes, which resulted in more hydrogen production. Adding catalysts, from 38 to 58%, 53 to 85%, was a rise in the simulated carbon conversion. Similarly, with adding catalysts, the simulated hydrogen output rose from 0.33 to 0.67, 0.76, and 1.07 mol (mol C)$^{-1}$, respectively. The results show that the ANN model was a reliable and effective method for predicting the production of hydrogen and the conversion of carbon during the gasification of catalytic coal in a fixed bed. It could also be used to produce hydrogen from other carbon resources.

The latest research by Kim et al., (2023) so as to estimate syngas compositions and LHV utilizing a variety of feedstocks made of lignocellulosic biomass under the usage of machine learning methods, including RF, SVM, and ANN, was done under a variety of operating situations. With high $R^2$ (RF: $R^2 = 0.809$–$0.946$, ANN: $R^2 = 0.565$–$0.924$), and reduced RSME (RF: RMSE = 1.39–11.54%; ANN: RMSE = 1.46–10.56%), the RF and ANN produced accurate predictions. In comparison, the SVM was unable to achieve an acceptable $R^2$ prediction accuracy. With $R^2$ (0.946, 0.896, 0.923, 0.906, 0.809, 0.884, 0.857 for $H_2$, CO, $CO_2$, $CH_4$, LHV, Char, and Tar, respectively) higher than those of SVM and ANN, the RF model predictions have often shown an excellent agreement with the observed data. The yield of methane and tar showed a negative relationship with temperature (0.474 and 0.353, respectively), indicating that the tar is more sensitive to decomposition and methane combustion at high temperatures. As a more excellent ER generates more $CO_2$, which lowers the LHV, ER shows solid critical relationships with an LHV. Furthermore, tar production and $CH_4$ negatively correlate with ER because higher ER promotes better oxidation, eventually increasing $CO_2$ formation. The fluidized bed-produced syngas had an ideal $H_2$/CO ratio greater than 1.1. Additionally, LHV > 5.86 MJ/m$^3$ allows syngas to function as an accessible intermediary in the synthesis of chemicals. With the use of machine learning methods, Monte Carlo filtering (MCF) was used to determine the feature relevance of the desired syngas composition and LHV. The RF-MCF method was more acceptable, with value of $R^2$ was between 0.791 and 0.902 for $H_2$, CO, and LHV characteristics.

To anticipate the gas composition produced and the LHV when gasifying woody biomass in a downdraft fixed bed generator MLP-NN model was used. According to experimental studies, raw materials with a lot of carbon and a lot of heat accelerated the cracking of tar due to heat and increased the production of synthesis gas. Also, the most successful parameter was nitrogen for $H_2$ and LHV outputs. Although N and S content in biomass is insignificant (less than 1.75% by weight), it can significantly affect the gases produced and the energy content of the gas. The concentrations of $H_2$, CO, and $CH_4$ increased due to the size of the particles decreasing. Also, the moisture content, Ash, volatile matter, and humidity had the most significant influence on the syngas component. The most important finding was that for all CO, $H_2$, $CH_4$, $CO_2$, $N_2$, and LHV outputs, operating parameters had a more significant impact than parameters describing the chemical and physical composition of the biomass. Regarding the distribution of reactor temperatures, for gases with calorific value, it can be said that temperatures in the pyrolysis and reduction zones were more significant, and the drying zone temperature was more effective for gases lacking calorific value. The findings demonstrate that the model became more accurate at forecasting the desired results as the hidden layer's number of neurons (more than 42) increased. Moreover, the transit function was selected as the final model because of its higher accuracy in predicting model outputs. The

findings demonstrated that The Levenberg–Marquardt algorithm with MLP architecture had a respectable level of accuracy in predicting the outputs. Functioning of the suggested MLP pattern demonstrated high that the output and target values agree with $R^2 > 0.952$, RMSE < 0.83, and rRMSE < 6.5%. Furthermore, the results demonstrated that the model of MLP can successfully substitute the expensive trial testing to investigate the gasification process (Hashem Samadi et al., 2023).

In another study, in order to increase $H_2$ generation, the gasification of MSW was evaluated using the ANN technique. Several conditions, including temperatures, MSW loadings, residence periods, and equivalency ratios, were used in the tests, which were carried out in a horizontal tube reactor. According to the result, for the training phase $R^2$ 0.939 and the evaluation stage, At the higher reaction temperature of 900 °C and LHV of 11.2 MJ/Nm$^3$, a larger $H_2$ generation of 42.1 vol% was generated. Finally, it is confirmed that the suggested model is a trustworthy tool for waste-to-energy applications to make crucial choices by choosing important parameters for higher $H_2$ generation from MSW gasification with little tar content (Jamro et al., 2023).

According to the studies that were previously presented, the studies confirmed that due to their ability to recognize extremely non-linear relationships between inputs and outputs, ANNs are ideally suited to describe the gasification process. For instance, the prediction of; $H_2$ yield, syngas composition, syngas yield, net out power, chemical exergy LHV, and carbon conversion was made using ANN-based models' efficiency. In all studies, there was a greater correlation coefficient between the predicted values of the ANN ($R^2$ 0.99). Furthermore, the GPR and GBR models demonstrated their high capacity for the prediction of $H_2$ yield, as the predicted values of these models had a higher correlation coefficient ($R^2$ 0.99). Similarly, when predicting syngas yield and composition, the GBR pattern attained high predictive accuracy of $R^2$ >0.99. Likewise, there was a high predictive value for the RF model when predicting the composition of syngas with $R^2$ greater than 0.95.

In general, in publications on gasification, it is possible to mention the major roles played by ANN, SVM, RF, GBR, DT, etc., algorithms. Additionally, several relatively recent DL algorithms with various features and advantages can be extensively applied in gasification. Some of these algorithms, like CNN, LSTM, GRU, etc., can be used in problems in gasification that are quite complex and sometimes lack data.

## Challenges and future insights

The use of AI techniques in the thermal conversion of biomass has been the subject of several studies. However, there are still significant information gaps; there is no doubt that we need additional extensive research to be investigated in future studies and the improvement of AI models. Applying AI to predict gas production and its components for biomass gasification provides challenges as well as opportunities. There will be significant works later as; enhancing the samples, improving the pattern to increase intelligence, and supporting improved industrial practices.

Applications of AI in gasification depend on the data's accessibility and quality, mainly produced by independent experimental research, which is expensive and wastes time, and literature data characterized by inconsistencies. For the design, operation, and optimization of gasification processes, reliable, high-quality data are required and more accessible (Ascher et al., 2022b). And so, it is necessary to propose policies to improve data quality and availability.

Most ML techniques are known as "black boxes." Thus, it is a great challenge to apply such methods to study methods and paths for gasification. Later research must focus on combining ML models with traditional modeling methods, such as kinetics investigations, on providing in-depth information on reaction mechanisms and pathways. Future work should aim to shed light on the ML algorithm's black-box structure to make it easier to understand. And so, it is simple to learn the relationship between the input and goal variables (Umenweke et al., 2022). Gray-box modeling could be used to investigate further and open the "black box" of machine learning. A Gray-box model combines a data-driven and partial theory-driven model, sometimes known as a first principal model (khan et al., 2023).

Deep learning has reached amazing results when presented with difficulties across a multiplicity of sectors. The central concept of DL is to raise the number of standard neural networks with three layers by increasing the number of layers and the number

of complicated interactions between the nodes inside those levels. The variety of DL networks makes them superior to conventional ML methods for many challenging thermal conversion processes. Despite the various benefits of DL models, DL-based models are frequently underutilized in thermal conversion processes, and this research knowledge gap may need to be filled (Khan et al., 2023).

In thermal conversion techniques, one AI method alone is not enough to be used because of each technique's different outputs and complexities. Whether paired with other ML algorithms, optimization algorithms, or sophisticated statistical tools, using AI models in gasification technology has produced promising outcomes (Elmaz et al., 2020; Khurram Faridi et al., 2022; B. Zhang et al., 2022). That is to say, there is a need to create standardized, useable processes for choosing the algorithm and the size of the data collection. And so, more case studies should be done on gasification systems with biomass feedstock.

Despite the fact that the amounts of N and S in the chemical composition of biomass are negligible (less than 1.75% by weight), a study by Hashem Samadi et al., (2023) demonstrated that even a tiny change in the N or S content of biomass could have a significant impact on the gases produced and the calorific value of the gas. Still, further research is required because there have not been enough studies on the effects of sulfur and nitrogen levels in feedstocks on syngas performance.

Finally, even while ML models are quite precise, they do not lend themselves well to interpretation, unlike models of thermodynamic equilibrium, for example, hence it has occasionally been challenging to understand modeling results. In order to enhance the processes' fundamental understanding and design capability, it is crucial to create more interpretable models (Ascher et al., 2022b). In addition, future research should assess deep learning DL application algorithms in biomass gasification for bioenergy production for more sophisticated predictions, control, and optimization.

## Conclusion

The current review conducted a comprehensive assessment and provided a detailed overview of the essential debates pertaining to the utilization of AI technology in the field of gasification research. Firstly, presents an extensive summary of the benefits and drawbacks associated with biomass conversion methods. Furthermore, this work provides a brief discussion of several ML and DL methods that have been employed in the field of gasification research. Furthermore, this work provides a brief discussion of several ML and DL methods that have been employed in the field of gasification research. The specific algorithms under consideration are ANN, SVM, DT, RF, CNN, GAN, AE, and RNN. The advantages and disadvantages of each algorithm are also discussed. Finally, a number of challenges and recommendations were presented to further the study of gasification using AI models. Several research directions and proposals that are worthy of further investigation are highlighted as follows:

- Currently, machine learning (ML) and deep learning (DL) algorithms are being used in gasification investigations, just as in other areas of life. The present field of research mostly focuses on analyzing variables such as gasification agent, temperature, pressure, and heat source. Researchers in this sector have great chances to use Artificial Intelligence (AI) approaches to simulate the impact of various factors on the efficiency of the process.
- The main goal of biomass gasification, from both an economic and environmental standpoint, goes beyond only focusing on the methods of producing tar and syngas. In an effective gasification process, biomass waste is not only disposed of but also contributes to environmental benefits. The gasification process is particularly advantageous in terms of decreasing carbon emissions and promoting the "carbon-zero" approach, making it ecologically beneficial. The gasification of waste offers economic advantages, such as obtaining valuable products and synthesis gas, and guarantees the sustainability of the gasification process. Focused research on the use of synthesis gas as an energy source helps achieve this sustainability.
- The gasification process produces synthesis gas, which is mostly composed of hydrogen ($H_2$). Researchers should perform extensive research into the mechanisms of $H_2$ formation and make efforts to improve $H_2$ production. machine learning (ML) and deep learning (DL) approaches

are essential for modeling systems at this level. Applying machine learning approaches to simulate the interactions between system characteristics will assist in the creation of more optimized designs.

- The primary study focuses on AI-based gasification studies revolves around the prediction of various key parameters, including hydrogen ($H_2$) yield, syngas composition, lower heating value (LHV), higher heating value (HHV), carbon conversion efficiency, syngas yield, biochar yield, and net output power. On the other hand, the ANN model is extensively employed in the field of gasification studies. The model exhibited a consistently high level of performance, with an *r*-squared value of more than 0.9 seen in nearly all studies.
- Overall, these days, many industries and applications related to energy conversion systems use AI algorithms. Predicting the output of conversion systems and subjects linked to optimization are two of this science's critical applications. The findings of this study demonstrate that AI models perform well enough for various uses.

**Abbreviations** *A*: Ash content; *ABR***:** AdaBoost regression; *Adj* $R^2$: Adjusted coefficient of determination; *AE*: Absolute error; *ANN*: Artificial neural networks; *BP*: BackPropagation; *CFBP*: Cascade-forward back propagation; *CFBP-GA*: Cascade-forward back propagation-genetic algorithm; *CHP*: Combined heat and power; *CNN*: Convolutional neural network; *DT*: Decision tree; *DTR*: Decision tree regression; *ET***:** Ensembled tree; *FBG*: Fluidized bed biomass gasifier; *FEBP*: Feed-forward back propagation; *GA*: Genetic algorithms; *GAN*: Generative adversative network; *GBR*: Gradient boost regressor; *GPR*: Gaussian process regression; *GRU*: Gated recurrent units; *HHV*: Higher heating value; *HTG*: Hydrothermal gasification; *LHV*: Lower heating value of gas; *LHVp*: Heating value of gasification products; *LM*: Levenberg-Marquardt; *LSTM*: Long short-term memory; *MAD*: Mean absolute deviation; *MAE*: Mean absolute error; *MAPE*: Mean absolute percentage error; *MC*: Moisture content; *MCF*: Monte Carlo filtering; *ME*: Mean error; *MLP*: Multilayer perceptron; *MRC*: Machine reading comprehension; *MSE*: Mean squared error; *MSW*: Municipal solid waste; *NLRQM*: Non-linear response quadratic model; *NRMSE*: Normalized root mean squared error; *OEM*: Optimized ensemble model; *OML*: Optimize machine learning; *PR*: Polynomial regression; *PSO*: Particle swarm optimization; $R^2$: Coefficient of determination; *RAE*: Relative absolute error; *RBF*: Radial basis function; *RE*: Reconstruction error; *RF*: Random forest; *RMSE*: Root means square error; *RNN*: Recurrent neural network; *RPE*: Relative percentage error; *SD*: Standard deviation; *SE*: Standard error; *SHAP*: Shapley Additive exPlanations; *SL*: Super learner; *SQP*: Sequential quadratic programming; *SVM*: Support vector machines; *SVR*: Support vector regression; *VM*: Volatile matter; *XGB*: Extreme gradient boosting

**Author contribution** Huseyin Kurtulus Ozcan: planning and supervising the work; Fatma Alfarra: investigation; Fatma Alfarra: writing—original draft preparation; Fatma Alfarra, Huseyin Kurtulus Ozcan, and Pınar Cihan designed and edited the figures; Fatma Alfarra, Huseyin Kurtulus Ozcan, Pınar Cihan, Atakan Ongen, Senem Yazıcı Güvenc, and Mirac Nur Ciner: writing—review and editing. All authors discussed the results and commented on the manuscript.

**Funding** This study was funded by the Scientific Research Projects Coordination Unit of Istanbul University-Cerrahpasa Rectorate. Project number: 37323.

**Declarations**

**Ethical approval** All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

**Competing interests** The authors declare no competing interests.

## References

Abdel-Jaber, H., Devassy, D., Al Salam, A., Hidaytallah, L., & El-Amir, M. (2022). A review of deep learning algorithms and their applications in healthcare. In *Algorithms* (Vol. 15, Issue 2). MDPI. https://doi.org/10.3390/a15020071

Afolabi, I. C., Popoola, S. I., & Bello, O. S. (2020). Modeling pseudo-second-order kinetics of orange peel-paracetamol adsorption process using artificial neural network. *Chemometrics and Intelligent Laboratory Systems*, *203*. https://doi.org/10.1016/j.chemolab.2020.104053

Aghbashlo, M., Peng, W., Tabatabaei, M., Kalogirou, S. A., Soltanian, S., Hosseinzadeh-Bandbafha, H., Mahian, O., & Lam, S. S. (2021). Machine learning technology in biodiesel research: A review. In *Progress in Energy and Combustion Science* (Vol. 85). Elsevier Ltd. https://doi.org/10.1016/j.pecs.2021.100904

Aguilar, D. L., Medina-Perez, M. A., Loyola-Gonzalez, O., Choo, K. K. R., & Bucheli-Susarrey, E. (2023). Towards an interpretable autoencoder: A decision-tree-based autoencoder and its application in anomaly detection. *IEEE Transactions on Dependable and Secure Computing, 20*(2), 1048–1059. https://doi.org/10.1109/TDSC.2022.3148331

Ahmed, S. F., Alam, M. S., Bin, H., Rozbu, M., Ishtiak, M. R., Rafa, T., Mofijur, N., Shawkat, M., Ali, A. B. M., & Gandomi, A. H. (2023). Deep learning modelling techniques: Current progress, applications, advantages, and challenges. *Artificial Intelligence Review*. https://doi.org/10.1007/s10462-023-10466-8

Ajorloo, M., Ghodrat, M., Scott, J., & Strezov, V. (2022). Recent advances in thermodynamic analysis of biomass gasification: A review on numerical modelling and simulation. In *Journal of the Energy Institute* (Vol. 102, pp. 395–419). Elsevier B.V. https://doi.org/10.1016/j.joei.2022.05.003

AkyolK, K., & Karaci, A. (2021). Diyabet Hastalığının Erken Aşamada Tahmin Edilmesi İçin Makine Öğrenme Algoritmalarının Performanslarının Karşılaştırılması. *Düzce Üniversitesi Bilim ve Teknoloji Dergisi, 9*(6), 123–134. https://doi.org/10.29130/dubited.1014508

Alaedini, A. H., Tourani, H. K., & Saidi, M. (2023). A review of waste-to-hydrogen conversion technologies for solid oxide fuel cell (SOFC) applications: Aspect of gasification process and catalyst development. In *Journal of Environmental Management* (Vol. 329). Academic Press. https://doi.org/10.1016/j.jenvman.2022.117077

Alain, G., Almahairi, A., Bahdanau, D., Bastien, F., Cho, K., Erhan, D., Fan, Z., Firat, O., Germain, M., Glorot, X., Goodfellow, I., Graham, M., Gulcehre, C., Hamel, P., Harlouchet, I., Heng, J.-P., Hidasi, B., Honari, S., Jain, A., … Zhang, Y. (2016). *Theano: A Python framework for fast computation of mathematical expressions*. http://arxiv.org/abs/1605.02688

Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., Alonso-Moral, J. M., Confalonieri, R., Guidotti, R., Del Ser, J., Díaz-Rodríguez, N., & Herrera, F. (2023). Explainable artificial intelligence (XAI): What we know and what is left to attain trustworthy artificial intelligence. *Information Fusion*. https://doi.org/10.1016/j.inffus.2023.101805

Alom, M. Z., Taha, T. M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M. S., Hasan, M., van Essen, B. C., Awwal, A. A. S., & Asari, V. K. (2019). A state-of-the-art survey on deep learning theory and architectures. In *Electronics (Switzerland)* (Vol. 8, Issue 3). MDPI AG. https://doi.org/10.3390/electronics8030292

Angeles, M. J., Leyva, C., Ancheyta, J., & Ramírez, S. (2014). A review of experimental procedures for heavy oil hydrocracking with dispersed catalyst. *Catalysis Today, 220–222*, 274–294. https://doi.org/10.1016/j.cattod.2013.08.016

Asaad, S. M., Inayat, A., Rocha-Meneses, L., Jamil, F., Ghenai, C., & Shanableh, A. (2023). Prospective of response surface methodology as an optimization tool for biomass gasification process. In *Energies* (Vol. 16, Issue 1). MDPI. https://doi.org/10.3390/en16010040

Asadi, A., Kadijani, O. N., Doranehgard, M. H., Bozorg, M. V., Xiong, Q., Shadloo, M. S., & Li, L. K. B. (2020). Numerical study on the application of biodiesel and bioethanol in a multiple injection diesel engine. *Renewable Energy, 150*, 1019–1029. https://doi.org/10.1016/j.renene.2019.11.088

Ascher, S., Wang, X., Watson, I., Sloan, W., & You, S. (2022a). Interpretable machine learning to model biomass and waste gasification. *Bioresource Technology, 364*, 128062. https://doi.org/10.1016/j.biortech.2022.128062

Ascher, S., Watson, I., & You, S. (2022b). Machine learning methods for modelling the gasification and pyrolysis of biomass and waste. In *Renewable and Sustainable Energy Reviews* (Vol. 155). Elsevier Ltd. https://doi.org/10.1016/j.rser.2021.111902

Ashwin, N. R., Cao, Z., Muralidhar, N., Tafti, D., & Karpatne, A. (2022). Deep learning methods for predicting fluid forces in dense particle suspensions. *Powder Technology, 401*. https://doi.org/10.1016/j.powtec.2022.117303

Ayodele, B. V., Mustapa, S. I., Kanthasamy, R., Zwawi, M., & Cheng, C. K. (2021). Modeling the prediction of hydrogen production by co-gasification of plastic and rubber wastes using machine learning algorithms. *International Journal of Energy Research, 45*(6), 9580–9594. https://doi.org/10.1002/er.6483

Ayodele, B. V., Mustapa, S. I., Kanthasamy, R., Mohammad, N., AlTurki, A., & Babu, T. S. (2022). Performance analysis of support vector machine, Gaussian process regression, sequential quadratic programming algorithms in modeling hydrogen-rich syngas production from catalyzed co-gasification of biomass wastes from oil palm. *International Journal of Hydrogen Energy*. https://doi.org/10.1016/j.ijhydene.2022.05.066

Bahadar, A., Kanthasamy, R., Sait, H. H., Zwawi, M., Algarni, M., Ayodele, B. V., Cheng, C. K., & Wei, L. J. (2022). Elucidating the effect of process parameters on the production of hydrogen-rich syngas by biomass and coal Co-gasification techniques: A multi-criteria modeling approach. *Chemosphere, 287*. https://doi.org/10.1016/j.chemosphere.2021.132052

Bank, D., Koenigstein, N., & Giryes, R. (2023). Autoencoders. *Machine Learning for Data Science Handbook*, 353–374. https://doi.org/10.1007/978-3-031-24628-9_16

Brophy, E., Wang, Z., She, Q., & Ward, T. (2023). Generative adversarial networks in time series: A systematic literature review. In *ACM Computing Surveys* (Vol. 55, Issue 10). Association for Computing Machinery. https://doi.org/10.1145/3559540

Chalermsinsuwan, B., Li, Y. H., & Manatura, K. (2023). Optimization of gasification process parameters for COVID-19 medical masks using response surface methodology. *Alexandria Engineering Journal, 62*, 335–347. https://doi.org/10.1016/j.aej.2022.07.037

Chen, W. H., Lin, B. J., Lin, Y. Y., Chu, Y. S., Ubando, A. T., Show, P. L., Ong, H. C., Chang, J. S., Ho, S. H., Culaba, A. B., Pétrissans, A., & Pétrissans, M. (2021). Progress in biomass torrefaction: Principles, applications and challenges. In *Progress in Energy and Combustion Science* (Vol. 82). Elsevier Ltd. https://doi.org/10.1016/j.pecs.2020.100887

Chen, Y., Yang, X. H., Wei, Z., Heidari, A. A., Zheng, N., Li, Z., Chen, H., Hu, H., Zhou, Q., & Guan, Q. (2022). Generative adversarial networks in medical image augmentation: A review. *Computers in Biology and Medicine*, *144*. https://doi.org/10.1016/j.compbiomed.2022.105382

Chilakamarry, C. R., Mimi Sakinah, A. M., Zularisam, A. W., Sirohi, R., Khilji, I. A., Ahmad, N., & Pandey, A. (2022). Advances in solid-state fermentation for bioconversion of agricultural wastes to value-added products: Opportunities and challenges. In *Bioresource Technology* (Vol. 343). Elsevier Ltd. https://doi.org/10.1016/j.biortech.2021.126065

Chu, C., Wang, P., Boré, A., Ma, W., Chen, G., & Wang, P. (2023a). Thermal plasma co-gasification of polyvinyl-chloride and biomass mixtures under steam atmospheres: Gasification characteristics and chlorine release behavior. *Energy, 262*, 125385. https://doi.org/10.1016/j.energy.2022.125385

Chu, Z., Li, Y., Zhang, C., Fang, Y., & Zhao, J. (2023b). A review on resource utilization of oil sludge based on pyrolysis and gasification. *Journal of Environmental Chemical Engineering*, 109692. https://doi.org/10.1016/j.jece.2023.109692

Cihan, P. (2022). The machine learning approach for predicting the number of intensive care, intubated patients and death: The COVID-19 pandemic in Turkey. *Sigma Journal of Engineering and Natural Sciences, 40*(1), 85–94. https://doi.org/10.14744/sigma.2022.00007

Cihan, P. (2023). Effect of parameter selection on heart attack risk prediction in an RNN model. *International Conference on Applied Engineering and Natural Sciences, 1*(1), 56–60. https://doi.org/10.59287/icaens.964

Cihan, P., Kalıpsız, O., & Gökçe, E. (2020). Computer-aided diagnosis in neonatal lambs. *Pamukkale University Journal of Engineering Sciences, 26*(2), 385–391. https://doi.org/10.5505/pajes.2019.51447

Cihan, P., Gökçe, E., Atakişi, O., Kirmizigül, A. H., & Erdoğan, H. M. (2021a). Prediction of immunoglobulin g in lambs with artificial intelligence methods. *Kafkas Universitesi Veteriner Fakultesi Dergisi, 27*(1), 21–27. https://doi.org/10.9775/kvfd.2020.24642

Cihan, P., & Ozger, Z. B. (2022). A new approach for determining SARS-CoV-2 epitopes using machine learning-based in silico methods. *Computational Biology and Chemistry*, *98*. https://doi.org/10.1016/j.compbiolchem.2022.107688

Cihan, P., Kalıpsız, O., & Gökçe, E. (2019). Effect of imputation methods in the classifier performance. *Sakarya University Journal of Science*, 1225–1236. https://doi.org/10.16984/saufenbilder.515716

Cihan, P., Ozel, H., & Ozcan, H. K. (2021b). Modeling of atmospheric particulate matters via artificial intelligence methods. *Environmental Monitoring and Assessment*, *193*(5). https://doi.org/10.1007/s10661-021-09091-1

Cihan, P. (2020). Deep learning-based approach for missing data imputation. *Eskişehir Teknik Üniversitesi Bilim ve Teknoloji Dergisi B - Teorik Bilimler*, *8*(2), 337–343. https://doi.org/10.20290/estubtdb.747821

Cihan, P. (2022a). Impact of the COVID-19 lockdowns on electricity and natural gas consumption in the different industrial zones and forecasting consumption amounts: Turkey case study. *International Journal of Electrical Power and Energy Systems*, *134*. https://doi.org/10.1016/j.ijepes.2021.107369

Cortazar, M., Santamaria, L., Lopez, G., Alvarez, J., Zhang, L., Wang, R., Bi, X., & Olazar, M. (2023). A comprehensive review of primary strategies for tar removal in biomass gasification. In *Energy Conversion and Management* (Vol. 276). Elsevier Ltd. https://doi.org/10.1016/j.enconman.2022.116496

Da'u, A., & Salim, N. (2020). Recommendation system based on deep learning methods: A systematic review and new directions. *Artificial Intelligence Review, 53*(4), 2709–2748. https://doi.org/10.1007/s10462-019-09744-1

Dong, M., Feng, L., & Qin, B. (2023). Characteristics of coal gasification with CO2 after microwave irradiation based on TGA. *FTIR and DFT Theory. Energy, 267*, 126619. https://doi.org/10.1016/j.energy.2023.126619

Duc Bui, V., Phuong Vu, H., Phuong Nguyen, H., Quang Duong, X., Tuyen Nguyen, D., Tuan Pham, M., & Quy Phong Nguyen, P. (2023). Techno-economic assessment and logistics management of biomass in the conversion progress to bioenergy. *Sustainable Energy Technologies and Assessments*, *55*. https://doi.org/10.1016/j.seta.2022.102991

Elmaz, F., Yücel, Ö., & Mutlu, A. Y. (2020). Predictive modeling of biomass gasification with machine learning-based regression methods. *Energy*, *191*. https://doi.org/10.1016/j.energy.2019.116541

Emmert-Streib, F., Yang, Z., Feng, H., Tripathi, S., & Dehmer, M. (2020). An introductory review of deep learning for prediction models with big data. In *Frontiers in Artificial Intelligence* (Vol. 3). Frontiers Media S.A. https://doi.org/10.3389/frai.2020.00004

Fang, Y., Ma, L., Yao, Z., Li, W., & You, S. (2022). Process optimization of biomass gasification with a Monte Carlo approach and random forest algorithm. *Energy Conversion and Management*, *264*. https://doi.org/10.1016/j.enconman.2022.115734

Forootan, M. M., Larki, I., Zahedi, R., & Ahmadi, A. (2022). machine learning and deep learning in energy systems: A review. In *Sustainability (Switzerland)* (Vol. 14, Issue 8). MDPI. https://doi.org/10.3390/su14084832

Fu, W., Zhang, Y., Cui, L., Liu, H., & Maqsood, T. (2023). Experimental microwave-assisted air gasification of biomass in fluidized bed reactor. *Bioresource Technology, 369*, 128378. https://doi.org/10.1016/j.biortech.2022.128378

García Nieto, P. J., García-Gonzalo, E., Sánchez Lasheras, F., Paredes-Sánchez, J. P., & Riesgo Fernández, P. (2019). Forecast of the higher heating value in biomass torrefaction by means of machine learning techniques. *Journal of Computational and Applied Mathematics, 357*, 284–301. https://doi.org/10.1016/j.cam.2019.03.009

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). *Generative adversarial nets*. https://github.com/goodfeli/adversarial. Accessed 18 Feb 2024.

Guan, Y., Chaffart, D., Liu, G., Tan, Z., Zhang, D., Wang, Y., Li, J., & Ricardez-Sandoval, L. (2022). Machine learning in solid heterogeneous catalysis: Recent developments,

challenges and perspectives. In *Chemical Engineering Science* (Vol. 248). Elsevier Ltd. https://doi.org/10.1016/j.ces.2021.117224

Gui, J., Sun, Z., Wen, Y., Tao, D., & Ye, J. (2023). A review on generative adversarial networks: Algorithms, theory, and applications. *IEEE Transactions on Knowledge and Data Engineering, 35*(4), 3313–3332. https://doi.org/10.1109/TKDE.2021.3130191

Guo, Q., Yan, B., Hu, Y., Guo, X., Wu, W., Cheng, Z., Chen, G., & Hou, L. (2023). A novel reutilization of ash from biomass gasification process: Feasibility and products improvement analysis. *Fuel, 339*, 127386. https://doi.org/10.1016/j.fuel.2022.127386

Guo, H. Nan, Wu, S. Biao, Tian, Y. Jie, Zhang, J., & Liu, H. Tao. (2021). Application of machine learning methods for the prediction of organic solid waste treatment and recycling processes: A review. In *Bioresource Technology* (Vol. 319). Elsevier Ltd. https://doi.org/10.1016/j.biortech.2020.124114

Halba, A., Vidyarthi, P. K., & Arora, P. (2022). Gasification as a potential solution for forest fires in the Indian Himalayan Region: A review. In *Bioresource Technology Reports* (Vol. 19). Elsevier Ltd. https://doi.org/10.1016/j.biteb.2022.101162

Hameed, Z., Aslam, M., Khan, Z., Maqsood, K., Atabani, A. E., Ghauri, M., Khurram, M. S., Rehan, M., & Nizami, A. S. (2021). Gasification of municipal solid waste blends with biomass for energy production and resources recovery: Current status, hybrid technologies and innovative prospects. *Renewable and Sustainable Energy Reviews*, *136*. https://doi.org/10.1016/j.rser.2020.110375

Haq, Z. U., Ullah, H., Khan, M. N. A., Naqvi, S. R., & Ahsan, M. (2022). Hydrogen production optimization from sewage sludge supercritical gasification process using machine learning methods integrated with genetic algorithm. *Chemical Engineering Research and Design, 184*, 614–626. https://doi.org/10.1016/j.cherd.2022.06.020

Hashem Samadi, S., Ghobadian, B., Nosrati, M., & Rezaei, M. (2023). Investigation of factors affecting performance of a downdraft fixed bed gasifier using optimized MLP neural networks approach. *Fuel*, *333*. https://doi.org/10.1016/j.fuel.2022.126249

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning* (2nd ed.). In Springer.

Huang, W., Zhang, R., Giannis, A., Li, C., & He, C. (2023). Sequential hydrothermal carbonization and CO2 gasification of sewage sludge for improved syngas production with mitigated emissions of NOx precursors. *Chemical Engineering Journal, 454*, 140239. https://doi.org/10.1016/j.cej.2022.140239

International Energy Agency (IEA). (2019). *Renewables 2019*. https://www.iea.org/reports/renewables-2019. Accessed 18 Feb 2024.

Jamro, I. A., Raheem, A., Khoso, S., Baloch, H. A., Kumar, A., Chen, G., Bhagat, W. A., Wenga, T., & Ma, W. (2023). Investigation of enhanced H2 production from municipal solid waste gasification via artificial neural network with data on tar compounds. *Journal of Environmental Management*, *328*. https://doi.org/10.1016/j.jenvman.2022.117014

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets, 31*, 685–695. https://doi.org/10.1007/s12525-021-00475-2/Published

Jiang, C., Jin, X., Xu, T., Xiao, B., Hu, Z., & Wang, X. (2023). Biomass chemical looping gasification for syngas production using modified hematite as oxygen carriers. *Journal of Environmental Sciences (china), 125*, 171–184. https://doi.org/10.1016/j.jes.2021.11.028

Jiang, W., & Luo, J. (2022). Graph neural network for traffic forecasting: A survey. In *Expert Systems with Applications* (Vol. 207). Elsevier Ltd. https://doi.org/10.1016/j.eswa.2022.117921

Kardani, N., Zhou, A., Nazem, M., & Lin, X. (2021). Modelling of municipal solid waste gasification using an optimised ensemble soft computing model. *Fuel*, *289*. https://doi.org/10.1016/j.fuel.2020.119903

Kargbo, H. O., Zhang, J., & Phan, A. N. (2021). Optimisation of two-stage biomass gasification for hydrogen production via artificial neural network. *Applied Energy*, *302*. https://doi.org/10.1016/j.apenergy.2021.117567

Kartal, F., & Özveren, U. (2020). A deep learning approach for prediction of syngas lower heating value from CFB gasifier in Aspen plus®. *Energy*, *209*. https://doi.org/10.1016/j.energy.2020.118457

Kartal, F., & Özveren, U. (2022a). Prediction of activation energy for combustion and pyrolysis by means of machine learning. *Thermal Science and Engineering Progress*, *33*. https://doi.org/10.1016/j.tsep.2022.101346

Kartal, F., & Özveren, U. (2022b). The dimensional design of a laboratory-scale fluidized bed gasifier using machine learning based on a kinetic method. *Energy Conversion and Management, 269*, 116183. https://doi.org/10.1016/j.enconman.2022.116183

Khan, M., Raza Naqvi, S., Ullah, Z., Ali Ammar Taqvi, S., Nouman Aslam Khan, M., Farooq, W., Taqi Mehran, M., Juchelková, D., & Štěpanec, L. (2023). Applications of machine learning in thermochemical conversion of biomass-A review. *Fuel*, *332*. https://doi.org/10.1016/j.fuel.2022.126055

Khurram Faridi, I., Tsotsas, E., Heineken, W., Koegler, M., & Kharaghani, A. (2022). Spatio-temporal prediction of temperature in fluidized bed biomass gasifier using dynamic recurrent neural network method. *Applied Thermal Engineering*, 119334. https://doi.org/10.1016/j.applthermaleng.2022.119334

Kim, J. Y., Kim, D., Li, Z. J., Dariva, C., Cao, Y., & Ellis, N. (2023). Predicting and optimizing syngas production from fluidized bed biomass gasifiers: A machine learning approach. *Energy*, *263*. https://doi.org/10.1016/j.energy.2022.125900

Kombe, E. Y., Lang'at, N., Njogu, P., Malessa, R., Weber, C. T., Njoka, F., & Krause, U. (2022). Process modeling and evaluation of optimal operating conditions for production of hydrogen-rich syngas from air gasification of rice husks using aspen plus and response surface methodology. *Bioresource Technology*, *361*. https://doi.org/10.1016/j.biortech.2022.127734

Kong, G., Wang, K., Zhang, X., Li, J., Han, L., & Zhang, X. (2022). Torrefaction/carbonization-enhanced gasification-steam reforming of biomass for promoting hydrogen-enriched syngas production and tar elimination

over gasification biochars. *Bioresource Technology*, *363*. https://doi.org/10.1016/j.biortech.2022.127960

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). *ImageNet classification with deep convolutional neural networks*. https://papers.nips.cc/paper_files/paper/2012/hash/c399862d3b9d6b76c8436e924a68c45b-Abstract.html. Accessed 18 Feb 2024.

Kumar Sharma, A., Kumar Ghodke, P., Goyal, N., Nethaji, S., & Chen, W.-H. (2022). Machine learning technology in biohydrogen production from agriculture waste: Recent advances and future perspectives. *Bioresource Technology, 364*, 128076. https://doi.org/10.1016/j.biortech.2022.128076

Kurian, V., Gill, M., Dhakal, B., & Kumar, A. (2022). Recent trends in the pyrolysis and gasification of lignocellulosic biomass. *Biofuels and Bioenergy: A Techno-Economic Approach*, 511–552. https://doi.org/10.1016/B978-0-323-90040-9.00028-X

Kushwah, A., Reina, T. R., & Short, M. (2022). Modelling approaches for biomass gasifiers: A comprehensive overview. In *Science of the Total Environment* (Vol. 834). Elsevier B.V. https://doi.org/10.1016/j.scitotenv.2022.155243

Lachos-Perez, D., César Torres-Mayanga, P., Abaide, E. R., Zabot, G. L., & de Castilhos, F. (2022). Hydrothermal carbonization and liquefaction: Differences, progress, challenges, and opportunities. In *Bioresource Technology* (Vol. 343). Elsevier Ltd. https://doi.org/10.1016/j.biortech.2021.126084

Li, W., & Song, Y. (2022). Artificial neural network model of catalytic coal gasification in fixed bed. *Journal of the Energy Institute*. https://doi.org/10.1016/j.joei.2022.08.012

Li, Z., Liu, F., Yang, W., Peng, S., & Zhou, J. (2022). A survey of convolutional neural networks: Analysis, applications, and prospects. *IEEE Transactions on Neural Networks and Learning Systems, 33*(12), 6999–7019. https://doi.org/10.1109/TNNLS.2021.3084827

Li, J., Pan, L., Suvarna, M., Tong, Y. W., & Wang, X. (2020). Machine learning prediction of syngas composition of hydrothermal gasification from wet organic wastes. In *International Conference on Applied Energy 2020*, 1–10 Dec, Bangkok, Thailand, Paper ID: 199. ICAE. https://doi.org/10.46855/energy-proceedings-7161

Li, J., Pan, L., Suvarna, M., & Wang, X. (2021a). Machine learning aided supercritical water gasification for H2-rich syngas production with process optimization and catalyst screening. *Chemical Engineering Journal*, *426*. https://doi.org/10.1016/j.cej.2021.131285

Li, J., Suvarna, M., Pan, L., Zhao, Y., & Wang, X. (2021b). A hybrid data-driven and mechanistic modelling approach for hydrothermal gasification. *Applied Energy*, *304*. https://doi.org/10.1016/j.apenergy.2021.117674

Li, J., Yao, X., & Xu, K. (2021c). A comprehensive model integrating BP neural network and RSM for the prediction and optimization of syngas quality. *Biomass and Bioenergy*, *155*. https://doi.org/10.1016/j.biombioe.2021.106278

Li, H., Li, M., Wang, H., Tan, M., Zhang, G., Huang, Z., & Yuan, X. (2023a). A review on migration and transformation of nitrogen during sewage sludge thermochemical treatment: Focusing on pyrolysis, gasification and combustion. In *Fuel Processing Technology* (Vol. 240). Elsevier B.V. https://doi.org/10.1016/j.fuproc.2022.107562

Li, J., Wang, H., Chen, H., Wu, H., Xu, G., Dong, Y., Zhao, Q., & Liu, T. (2023b). Comparative thermodynamic and techno-economic analysis of various medical waste-to-hydrogen/methanol pathways based on plasma gasification. *Applied Thermal Engineering*, *221*. https://doi.org/10.1016/j.applthermaleng.2022.119762

Lian, Z., Wang, Y., Zhang, X., Yusuf, A., Famiyeh, Lord, Murindababisha, D., Jin, H., Liu, Y., He, J., Wang, Y., Yang, G., & Sun, Y. (2021). Hydrogen production by fluidized bed reactors: A quantitative perspective using the supervised machine learning approach. *J*, *4*(3), 266–287. https://doi.org/10.3390/j4030022

Liang, J., Liu, Y., Chen, J., E, J., Leng, E., Zhang, F., & Liao, G. (2023). Performance comparison of black liquor gasification and oxidation in supercritical water from thermodynamic, environmental, and techno-economic perspectives. *Fuel*, *334*. https://doi.org/10.1016/j.fuel.2022.126787

Liao, M., & Yao, Y. (2021). Applications of artificial intelligence-based modeling for bioenergy systems: A review. In *GCB Bioenergy* (Vol. 13, Issue 5, pp. 774–802). Blackwell Publishing Ltd. https://doi.org/10.1111/gcbb.12816

Lin, E., Lin, C. H., & Lane, H. Y. (2021). Deep learning with neuroimaging and genomics in Alzheimer's disease. In *International Journal of Molecular Sciences* (Vol. 22, Issue 15). MDPI. https://doi.org/10.3390/ijms22157911

Lin, K., Zhao, Y., Kuo, J. H., Deng, H., Cui, F., Zhang, Z., Zhang, M., Zhao, C., Gao, X., Zhou, T., & Wang, T. (2022). Toward smarter management and recovery of municipal solid waste: A critical review on deep learning approaches. In *Journal of Cleaner Production* (Vol. 346). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2022.130943

Liu, C., Chen, D., Tang, Q., Abuelgasim, S., Xu, C., Wang, W., Luo, J., Zhao, Z., Abdalazeez, A., & Zhang, R. (2023b). Chemical looping gasification of biomass char for hydrogen-rich syngas production via Mn-doped Fe2O3 oxygen carrier. *International Journal of Hydrogen Energy*. https://doi.org/10.1016/j.ijhydene.2022.12.190

Liu, S., Yang, Y., Yu, L., Zhu, F., Cao, Y., Liu, X., Yao, A., & Cao, Y. (2022). Predicting gas production by supercritical water gasification of coal using machine learning. *Fuel*, *329*. https://doi.org/10.1016/j.fuel.2022.125478

Liu, C., Chen, D., Tang, Q., Abuelgasim, S., Xu, C., Luo, J., Zhao, Z., & Abdalazeez, A. (2023a). Hydrogen-rich syngas production from straw char by chemical looping gasification: The synergistic effect of Mn and Fe on Ni-based spinel structure as oxygen carrier. *Fuel*, *334*. https://doi.org/10.1016/j.fuel.2022.126803

Liu, Q., Zhao, Y. jie, Huang, Y., Pei, F., Cui, Y., Shi, L. juan, Chang, L. ping, & Yi, Q. (2023c). Pilot test of low-rank coal pyrolysis coupled with gasification to hydrogen-rich gas for direct reduced iron: Process modeling, simulation and thermodynamic analysis. *Fuel*, *331*. https://doi.org/10.1016/j.fuel.2022.125862

Liu, X., Shen, J., Guo, Y., Wang, S., Chen, B., Luo, L., & Zhang, H. (2023d). Technical progress and perspective on the thermochemical conversion of kitchen waste and relevant applications: A comprehensive review. In *Fuel* (Vol. 331). Elsevier Ltd. https://doi.org/10.1016/j.fuel.2022.125803

Lu, B., Bai, B., Zhang, R., Ma, J., Mao, L., Shi, J., & Jin, H. (2023). Study on gasification characteristics and kinetics of polyformaldehyde plastics in supercritical water. *Journal of Cleaner Production*, *383*. https://doi.org/10.1016/j.jclepro.2022.135459

Mahmoud, H. A. H., Hakami, N. A., & Hafez, A. M. (2022). An intelligent deep learning model for CO2 adsorption prediction. *Adsorption Science and Technology*, *2022*. https://doi.org/10.1155/2022/8136302

Maitlo, G., Ali, I., Mangi, K. H., Ali, S., Maitlo, H. A., Unar, I. N., & Pirzada, A. M. (2022). Thermochemical conversion of biomass for syngas production: Current status and future trends. In *Sustainability (Switzerland)* (Vol. 14, Issue 5). MDPI. https://doi.org/10.3390/su14052596

Manatura, K., Chalermsinsuwan, B., Kaewtrakulchai, N., Kwon, E. E., & Chen, W. H. (2023). Machine learning and statistical analysis for biomass torrefaction: A review. In *Bioresource Technology* (Vol. 369). Elsevier Ltd. https://doi.org/10.1016/j.biortech.2022.128504

Martins, A. H., Rouboa, A., & Monteiro, E. (2023). On the green hydrogen production through gasification processes: A techno-economic approach. *Journal of Cleaner Production*, *383*. https://doi.org/10.1016/j.jclepro.2022.135476

Mazzoni, L., Janajreh, I., Elagroudy, S., & Ghenai, C. (2020). Modeling of plasma and entrained flow co-gasification of MSW and petroleum sludge. *Energy*, *196*. https://doi.org/10.1016/j.energy.2020.117001

Mishra, K., Singh Siwal, S., Kumar Saini, A., & Thakur, V. K. (2023). Recent update on gasification and pyrolysis processes of lignocellulosic and algal biomass for hydrogen production. *Fuel*, *332*. https://doi.org/10.1016/j.fuel.2022.126169

Mishra, S., & Upadhyay, R. K. (2021). Review on biomass gasification: Gasifiers, gasifying mediums, and operational parameters. *Materials Science for Energy Technologies, 4*, 329–340. https://doi.org/10.1016/j.mset.2021.08.009

Mu, L., Wang, R., Xie, P., Li, Y., Huang, X., Yin, H., & Dong, M. (2023). Comparative investigation on the pyrolysis of crop, woody, and herbaceous biomass: Pyrolytic products, structural characteristics, and CO2 gasification. *Fuel*, *335*. https://doi.org/10.1016/j.fuel.2022.126940

Mukherjee, A., Bruijnincx, P., & Junginger, M. (2023). Techno-economic competitiveness of renewable fuel alternatives in the marine sector. *Renewable and Sustainable Energy Reviews*, *174*. https://doi.org/10.1016/j.rser.2022.113127

Mutlu, A. Y., & Yucel, O. (2018). An artificial intelligence based approach to predicting syngas composition for downdraft biomass gasification. *Energy, 165*, 895–901. https://doi.org/10.1016/j.energy.2018.09.131

Nam, K. J., Hwangbo, S., & Yoo, C. K. (2020). A deep learning-based forecasting model for renewable energy scenarios to guide sustainable energy policy: A case study of Korea. *Renewable and Sustainable Energy Reviews*, *122*. https://doi.org/10.1016/j.rser.2020.109725

Narayan, V., Awasthi, S., Fatima, N., Faiz, M., & Srivastava, S. (2023). Deep learning approaches for human gait recognition: A review. *2023 International Conference on Artificial Intelligence and Smart Communication, AISC 2023*, 763–768. https://doi.org/10.1109/AISC56616.2023.10085665

Norwegian Ministry of Climate and Environment (NMCE). (2019). *Norway's National Plan related to the Decision of the EEA Joint Committee No. 269/2019 of 25 October 2019. Norwegian Ministry of Climate and Environment.*

Nowakowski, P., & Pamuła, T. (2020). Application of deep learning object classifier to improve e-waste collection planning. *Waste Management, 109*, 1–9. https://doi.org/10.1016/j.wasman.2020.04.041

Nunes, L. J. R. (2022). Biomass gasification as an industrial process with effective proof-of-concept: A comprehensive review on technologies, processes and future developments. In *Results in Engineering* (Vol. 14). Elsevier B.V. https://doi.org/10.1016/j.rineng.2022.100408

Okati, A., Reza Khani, M., Shokri, B., Rouboa, A., & Monteiro, E. (2022). Optimizing the operating conditions for hydrogen-rich syngas production in a plasma co-gasification process of municipal solid waste and coal using Aspen Plus. *International Journal of Hydrogen Energy, 47*(63), 26891–26900. https://doi.org/10.1016/j.ijhydene.2022.06.058

Okati, A., Khani, M. R., Shokri, B., Monteiro, E., & Rouboa, A. (2023a). On the operating parameters for hydrogen-rich syngas production in a plasma co-gasification process of municipal solid wastes and polypropylene using a constrained model in Aspen plus. *Journal of the Energy Institute*, 101173. https://doi.org/10.1016/j.joei.2023.101173

Okati, A., Reza Khani, M., Shokri, B., Monteiro, E., & Rouboa, A. (2023b). Parametric studies over a plasma co-gasification process of biomass and coal through a restricted model in Aspen plus. *Fuel*, *331*. https://doi.org/10.1016/j.fuel.2022.125952

Ozbas, E. E., Aksu, D., Ongen, A., Aydin, M. A., & Ozcan, H. K. (2019). Hydrogen production via biomass gasification, and modeling by supervised machine learning algorithms. *International Journal of Hydrogen Energy, 44*(32), 17260–17268. https://doi.org/10.1016/j.ijhydene.2019.02.108

Özveren, U., Kartal, F., Sezer, S., & Özdoğan, Z. S. (2022). Investigation of steam gasification in thermogravimetric analysis by means of evolved gas analysis and machine learning. *Energy*, *239*. https://doi.org/10.1016/j.energy.2021.122232

Pan, Z., Wang, Y., Wang, K., Chen, H., Yang, C., & Gui, W. (2023). Imputation of missing values in time series using an adaptive-learned median-filled deep autoencoder. *IEEE Transactions on Cybernetics, 53*(2), 695–706. https://doi.org/10.1109/TCYB.2022.3167995

Papa, A. A., Savuto, E., Carlo, Di., di, A., Tacconi, A., & Rapagnà, S. (2023). Synergic effects of bed materials and catalytic filter candle for the conversion of tar during biomass steam gasification. *Energies, 16*(2), 595. https://doi.org/10.3390/en16020595

Pomeroy, B., Grilc, M., & Likozar, B. (2022). Artificial neural networks for bio-based chemical production or biorefining: A review. *Renewable and Sustainable Energy Reviews*, *153*. https://doi.org/10.1016/j.rser.2021.111748

Pu, Y., Apel, D. B., Liu, V., & Mitri, H. (2019). Machine learning methods for rockburst prediction-state-of-the-art

review. *International Journal of Mining Science and Technology, 29*(4), 565–570. https://doi.org/10.1016/j.ijmst.2019.06.009

Qian, L., Ni, J., Xu, W., Yuan, C., Wang, S., Hu, Y., & Gu, H. (2023). Phycocyanin to biocrude via the integration of isothermal/fast hydrothermal liquefaction and aqueous phase recirculation: Reaction products and process analyses. *Fuel*, *332*. https://doi.org/10.1016/j.fuel.2022.126226

Qianshi, S., Wei, Z., Xiaowei, W., Xiaohan, W., Haowen, L., Zixin, Y., Yue, Y., & Guangqian, L. (2023). Comprehensive effects of different inorganic elements on initial biomass char-CO2 gasification reactivity in micro fluidised bed reactor: Theoretical modeling and experiment analysis. *Energy*, *262*. https://doi.org/10.1016/j.energy.2022.125379

Ramos, J. S., & Ferreira, A. F. (2022). Techno-economic analysis and life cycle assessment of olive and wine industry co-products valorisation. *Renewable and Sustainable Energy Reviews*, *155*. https://doi.org/10.1016/j.rser.2021.111929

Ranzato, M. 'A, Hinton, G., & LeCun, Y. (2015). Guest editorial: Deep learning. In *International Journal of Computer Vision* (Vol. 113, Issue 1, pp. 1–2). Kluwer Academic Publishers. https://doi.org/10.1007/s11263-015-0813-1

Raschka, S. (2020). *Model evaluation, model selection, and algorithm selection in machine learning*. http://arxiv.org/abs/1811.12808. Accessed 18 Feb 2024.

Saeed, M. N., Shahrivar, M., Surywanshi, G. D., Kumar, T. R., Mattisson, T., & Soleimanisalim, A. H. (2023). Production of aviation fuel with negative emissions via chemical looping gasification of biogenic residues: Full chain process modelling and techno-economic analysis. *Fuel Processing Technology*, *241*. https://doi.org/10.1016/j.fuproc.2022.107585

Safarian, S., Unnþórsson, R., & Richter, C. (2019). A review of biomass gasification modelling. In *Renewable and Sustainable Energy Reviews* (Vol. 110, pp. 378–391). Elsevier Ltd. https://doi.org/10.1016/j.rser.2019.05.003

Safarian, S., Ebrahimi Saryazdi, S. M., Unnthorsson, R., & Richter, C. (2020). Artificial neural network integrated with thermodynamic equilibrium modeling of downdraft biomass gasification-power production plant. *Energy*, *213*. https://doi.org/10.1016/j.energy.2020.118800

Safarian, S., Ebrahimi Saryazdi, S. M., Unnthorsson, R., & Richter, C. (2021). Modeling of hydrogen production by applying biomass gasification: Artificial neural network modeling approach. *Fermentation*, *7*(2). https://doi.org/10.3390/fermentation7020071

Sajid, M., Raheem, A., Ullah, N., Asim, M., Ur Rehman, M. S., & Ali, N. (2022). Gasification of municipal solid waste: Progress, challenges, and prospects. In *Renewable and Sustainable Energy Reviews* (Vol. 168). Elsevier Ltd. https://doi.org/10.1016/j.rser.2022.112815

Salem, A. M., Dhami, H. S., & Paul, M. C. (2022). Syngas production and combined heat and power from Scottish agricultural waste gasification—A computational study. *Sustainability (Switzerland)*, *14*(7). https://doi.org/10.3390/su14073745

Sansaniwal, S. K., Pal, K., Rosen, M. A., & Tyagi, S. K. (2017). Recent advances in the development of biomass gasification technology: A comprehensive review. In *Renewable and Sustainable Energy Reviews* (Vol. 72, pp. 363–384). Elsevier Ltd. https://doi.org/10.1016/j.rser.2017.01.038

Santoyo-Castelazo, E., Santoyo, E., Zurita-García, L., Camacho Luengas, D. A., & Solano-Olivares, K. (2023). Life cycle assessment of bioethanol production from sugarcane bagasse using a gasification conversion process: Bibliometric analysis, systematic literature review and a case study. *Applied Thermal Engineering*, *219*. https://doi.org/10.1016/j.applthermaleng.2022.119414

Saravanan, A., Karishma, S., Senthil Kumar, P., & Rangasamy, G. (2023). A review on regeneration of biowaste into bioproducts and bioenergy: Life cycle assessment and circular economy. *Fuel*, *338*. https://doi.org/10.1016/j.fuel.2022.127221

Sarvamangala, D. R., & Kulkarni, R. V. (2022). Convolutional neural networks in medical image understanding: a survey. In *Evolutionary Intelligence* (Vol. 15, Issue 1). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/s12065-020-00540-3

Sedej, O., Mbonimpa, E., Sleight, T., & Slagley, J. (2022). Artificial neural networks and gradient boosted machines used for regression to evaluate gasification processes: A review. *Journal of Energy and Power Technology*, *4*(3), 1–1. https://doi.org/10.21926/jept.2203027

Seo, M. W., Lee, S. H., Nam, H., Lee, D., Tokmurzin, D., Wang, S., & Park, Y. K. (2022). Recent advances of thermochemical conversieon processes for biorefinery. In *Bioresource Technology* (Vol. 343). Elsevier Ltd. https://doi.org/10.1016/j.biortech.2021.126109

Sezer, S., Kartal, F., & Özveren, U. (2021). Prediction of chemical exergy of syngas from downdraft gasifier by means of machine learning. *Thermal Science and Engineering Progress*, *26*. https://doi.org/10.1016/j.tsep.2021.101031

Sezer, S., & Özveren, U. (2021). Investigation of syngas exergy value and hydrogen concentration in syngas from biomass gasification in a bubbling fluidized bed gasifier by using machine learning. *International Journal of Hydrogen Energy, 46*(39), 20377–20396. https://doi.org/10.1016/j.ijhydene.2021.03.184

Shafizadeh, A., Shahbeig, H., Nadian, M. H., Mobli, H., Dowlati, M., Gupta, V. K., Peng, W., Lam, S. S., Tabatabaei, M., & Aghbashlo, M. (2022). Machine learning predicts and optimizes hydrothermal liquefaction of biomass. *Chemical Engineering Journal*, *445*. https://doi.org/10.1016/j.cej.2022.136579

Shahabuddin, M., & Alam, T. (2022). Gasification of solid fuels (coal, biomass and MSW): Overview, challenges and mitigation strategies. In *Energies* (Vol. 15, Issue 12). MDPI. https://doi.org/10.3390/en15124444

Shahabuddin, M., Alam, M. T., Krishna, B. B., Bhaskar, T., & Perkins, G. (2020). A review on the production of renewable aviation fuels from the gasification of biomass and residual wastes. In *Bioresource Technology* (Vol. 312). Elsevier Ltd. https://doi.org/10.1016/j.biortech.2020.123596

Shahbeig, H., Shafizadeh, A., Rosen, M. A., & Sels, B. F. (2022). Exergy sustainability analysis of biomass gasification: a critical review. *Biofuel Research Journal*, *9*(1), 1592–1607. https://doi.org/10.18331/BRJ2022.9.1.5

Sharkawy, Abdel-Nasser. (2020). Principle of neural network and its main types: Review. *Journal of Advances in Applied & Computational Mathematics, 7*, 8–19. https://doi.org/10.15377/2409-5761.2020.07.2

Sharma, K. G., Kaisare, N. S., & Goyal, H. (2022). A recurrent neural network model for biomass gasification chemistry. *Reaction Chemistry and Engineering, 7*(3), 570–579. https://doi.org/10.1039/d1re00409c

Sharma, P., Sheth, P. N., & Mohapatra, B. N. (2023). Co-processing of petcoke and producer gas obtained from RDF gasification in a white cement plant: A techno-economic analysis. *Energy*, *265*. https://doi.org/10.1016/j.energy.2022.126248

Sidek, F. N., Abdul Samad, N. A. F., & Saleh, S. (2020). Review on effects of gasifying agents, temperature and equivalence ratio in biomass gasification process. *IOP Conference Series: Materials Science and Engineering*, *863*(1). https://doi.org/10.1088/1757-899X/863/1/012028

Song, H., Yang, G., Xue, P., Li, Y., Zou, J., Wang, S., Yang, H., & Chen, H. (2022). Recent development of biomass gasification for H2 rich gas production. *Applications in Energy and Combustion Science*, *10*. https://doi.org/10.1016/j.jaecs.2022.100059

Sun, C., Ai, L., & Liu, T. (2022). The PSO-ANN modeling study of highly valuable material and energy production by gasification of solid waste: An artificial intelligence algorithm approach. *Biomass Conversion and Biorefinery*. https://doi.org/10.1007/s13399-022-02342-2

Swiecki, Z., Khosravi, H., Chen, G., Martinez-Maldonado, R., Lodge, J. M., Milligan, S., Selwyn, N., & Gašević, D. (2022). Assessment in the age of artificial intelligence. *Computers and Education: Artificial Intelligence*, *3*. https://doi.org/10.1016/j.caeai.2022.100075

Tang, Q., Chen, Y., Yang, H., Liu, M., Xiao, H., Wu, Z., Chen, H., & Naqvi, S. R. (2020). Prediction of bio-oil yield and hydrogen contents based on machine learning method: Effect of biomass compositions and pyrolysis conditions. *Energy and Fuels, 34*(9), 11050–11060. https://doi.org/10.1021/acs.energyfuels.0c01893

Taoufik, N., Boumya, W., Achak, M., Chennouk, H., Dewil, R., & Barka, N. (2022). The state of art on the prediction of efficiency and modeling of the processes of pollutants removal based on machine learning. In *Science of the Total Environment* (Vol. 807). Elsevier B.V. https://doi.org/10.1016/j.scitotenv.2021.150554

Taye, M. M. (2023). Understanding of machine learning with deep learning: Architectures, workflow, applications and future directions. In *Computers* (Vol. 12, Issue 5). MDPI. https://doi.org/10.3390/computers12050091

Tezer, Ö., Karabağ, N., Öngen, A., Çolpan, C. Ö., & Ayol, A. (2022). Biomass gasification for sustainable energy production: A review. *International Journal of Hydrogen Energy*. https://doi.org/10.1016/j.ijhydene.2022.02.158

Tran, T. T. K., Bateni, S. M., Ki, S. J., & Vosoughifar, H. (2021). A review of neural networks for air temperature forecasting. In *Water (Switzerland)* (Vol. 13, Issue 9). MDPI AG. https://doi.org/10.3390/w13091294

Tullo, A. (2016). Air Products retreats from waste-to-energy. *C&EN Global Enterprise, 94*(15), 12–12. https://doi.org/10.1021/CEN-09415-NOTW12

Ugwu, L. I., Morgan, Y., & Ibrahim, H. (2022). Application of density functional theory and machine learning in heterogenous-based catalytic reactions for hydrogen production. In *International Journal of Hydrogen Energy* (Vol. 47, Issue 4, pp. 2245–2267). Elsevier Ltd. https://doi.org/10.1016/j.ijhydene.2021.10.208

Umenweke, G. C., Afolabi, I. C., Epelle, E. I., & Okolie, J. A. (2022). Machine learning methods for modeling conventional and hydrothermal gasification of waste biomass: A review. In *Bioresource Technology Reports* (Vol. 17). Elsevier Ltd. https://doi.org/10.1016/j.biteb.2022.100976

Umenweke, G. C., Pace, R. B., Santillan-Jimenez, E., & Okolie, J. A. (2023). Techno-economic and life-cycle analyses of sustainable aviation fuel production via integrated catalytic deoxygenation and hydrothermal gasification. *Chemical Engineering Journal*, *452*. https://doi.org/10.1016/j.cej.2022.139215

*Understanding Artificial Neural Networks | by Trist'n Joseph | Towards Data Science*. (2020). https://towardsdatascience.com/understanding-artificial-neural-networks-3fc3cbcd397d. Accessed 18 Feb 2024.

Vamvuka, D., Tzilivakos, P., Afthentopoulos, E., & Chatzifotiadis, H. (2023). Comparative study on the gasification performance of two energy crops by steam or carbon dioxide. *Bioresource Technology Reports*, 101320. https://doi.org/10.1016/j.biteb.2022.101320

Vinitha, N., Vasudevan, J., & Gopinath, K. P. (2022). Bioethanol production optimization through machine learning algorithm approach: Biomass characteristics, saccharification, and fermentation conditions for enzymatic hydrolysis. *Biomass Conversion and Biorefinery*. https://doi.org/10.1007/s13399-022-03163-z

Wang, M. W. H., Goodman, J. M., & Allen, T. E. H. (2021). Machine learning in predictive toxicology: Recent applications and future directions for classification models. In *Chemical Research in Toxicology* (Vol. 34, Issue 2, pp. 217–239). American Chemical Society. https://doi.org/10.1021/acs.chemrestox.0c00316

Wu, Y., Wang, H., Li, H., Han, X., Zhang, M., Sun, Y., Fan, X., Tu, R., Zeng, Y., Xu, C. C., & Xu, X. (2022). Applications of catalysts in thermochemical conversion of biomass (pyrolysis, hydrothermal liquefaction and gasification): A critical review. In *Renewable Energy* (Vol. 196, pp. 462–481). Elsevier Ltd. https://doi.org/10.1016/j.renene.2022.07.031

Wu, N., Lan, K., & Yao, Y. (2023). An integrated techno-economic and environmental assessment for carbon capture in hydrogen production by biomass gasification. *Resources, Conservation and Recycling*, *188*. https://doi.org/10.1016/j.resconrec.2022.106693

Yan, B., Li, S., Cao, X., Zhu, X., Li, J., Zhou, S., Zhao, J., Sun, Y., & Chen, G. (2023). Flue gas torrefaction integrated with gasification based on the circulation of Mg-additive. *Applied Energy, 333*, 120612. https://doi.org/10.1016/j.apenergy.2022.120612

Yan, M., Liu, Y., Song, Y., Xu, A., Zhu, G., Jiang, J., & Hantoko, D. (2022). Comprehensive experimental study on energy conversion of household kitchen waste via integrated hydrothermal carbonization and supercritical water gasification. *Energy*, *242*. https://doi.org/10.1016/j.energy.2021.123054

Yang, J., Li, Y., Tan, H., Bian, J., & Cao, X. (2023). Optimization and analysis of a hydrogen liquefaction process integrated with the liquefied natural gas gasification and organic Rankine cycle. *Journal of Energy Storage*, *59*. https://doi.org/10.1016/j.est.2022.106490

Ye, Z., Yang, J., Zhong, N., Tu, X., Jia, J., & Wang, J. (2020). Tackling environmental challenges in pollution controls using artificial intelligence: A review. In *Science of the Total Environment* (Vol. 699). Elsevier B.V. https://doi.org/10.1016/j.scitotenv.2019.134279

Yim, H., Valizadeh, S., Pyo, S., Jang, S.-H., Ko, C. H., Khan, M. A., Jeon, B.-H., Lin, K.-Y.A., & Park, Y.-K. (2023). Hydrogen generation from gasification of woody biomass upon acid mine drainage sludge as a novel catalyst under an air medium. *Fuel, 338*, 127243. https://doi.org/10.1016/j.fuel.2022.127243

You, A., Kim, J. K., Ryu, I. H., & Yoo, T. K. (2022). Application of generative adversarial networks (GAN) for ophthalmology image domains: A survey. In *Eye and Vision* (Vol. 9, Issue 1). BioMed Central Ltd. https://doi.org/10.1186/s40662-022-00277-3

Yu, D., Hu, J., Wang, W., & Gu, B. (2023). Comprehensive techno-economic investigation of biomass gasification and nanomaterial based SOFC/SOEC hydrogen production system. *Fuel*, *333*. https://doi.org/10.1016/j.fuel.2022.126442

Zalazar-Garcia, D., Fernandez, A., Rodriguez-Ortiz, L., Rodriguez, R., & Mazza, G. (2022). Sustainable slow-pyrolysis simulation of 12 lignocellulosic bio-wastes: CO2 emission, energy, and water consumption. *IOP Conference Series: Earth and Environmental Science*, *952*(1). https://doi.org/10.1088/1755-1315/952/1/012008

Zang, G., Zhang, J., Ratner, A., & Shi, Y. (2023). Techno-economic analysis of a cooling, heating, and electricity trigeneration system based on downdraft fixed bed wood and tire gasification: Case study of a campus office building. *Sustainable Energy Technologies and Assessments*, *55*. https://doi.org/10.1016/j.seta.2022.102939

Zhai, S., Li, M., Xiong, Y., Wang, D., & Fu, S. (2020). Dual resource utilization for tannery sludge: Effects of sludge biochars (BCs) on volatile fatty acids (VFAs) production from sludge anaerobic digestion. *Bioresource Technology*, *316*. https://doi.org/10.1016/j.biortech.2020.123903

Zhang, Y., Xu, P., Liang, S., Liu, B., Shuai, Y., & Li, B. (2019). Exergy analysis of hydrogen production from steam gasification of biomass: A review. *International Journal of Hydrogen Energy, 44*(28), 14290–14302. https://doi.org/10.1016/j.ijhydene.2019.02.064

Zhang, B., Guo, S., & Jin, H. (2022). Production forecast analysis of BP neural network based on Yimin lignite supercritical water gasification experiment results. *Energy*, *246*. https://doi.org/10.1016/j.energy.2022.123306

Zhao, S., Li, J., Chen, C., Yan, B., Tao, J., & Chen, G. (2021). Interpretable machine learning for predicting and evaluating hydrogen production via supercritical water gasification of biomass. *Journal of Cleaner Production*, *316*. https://doi.org/10.1016/j.jclepro.2021.128244

Zhao, S., Xu, W., & Chen, L. (2022). The modeling and products prediction for biomass oxidative pyrolysis based on PSO-ANN method: An artificial intelligence algorithm approach. *Fuel*, *312*. https://doi.org/10.1016/j.fuel.2021.122966

Zheng, C., Zheng, C., Su, M., & Zhao, H. (2023). The competition/inhibition effect of H2O/CO2-char gasification in typical in situ gasification-chemical looping combustion (iG-CLC) conditions via particle-resolved simulation. *Fuel, 333*, 126316. https://doi.org/10.1016/j.fuel.2022.126316

Zheng, Z.-H., Lin, X.-D., Yang, M., He, Z.-M., Bao, E., Zhang, H., & Tian, Z.-Y. (2020). Progress in the application of machine learning in combustion studies. *ES Energy & Environment*. https://doi.org/10.30919/esee8c795

Ziółkowski, P., Stasiak, K., Amiri, M., & Mikielewicz, D. (2023). Negative carbon dioxide gas power plant integrated with gasification of sewage sludge. *Energy*, *262*. https://doi.org/10.1016/j.energy.2022.125496