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Downdraft Gasification for Biogas Production: The Role of Artificial Intelligence

Artificial intelligence (AI) can help improve many areas of waste management and biogas generation. The world has reached a state where waste generation is increasing daily, while an effective waste management system is essential for the sustainable development of a country. AI could be of great use in optimizing the waste management scheme by technical differentiation of all sorts and recycling techniques. AI can contribute to the improvement of waste segmentation, recycling, and disposal. Thus, by assessing availability and composition, AI can easily contribute to the selection of the most suitable feedstock for biogas generation. This paper will discuss the optimization of gasifier design, an important part of biogas production, to enhance gasification efficiency for more efficient syngas production. Several gains accrue from AI applications, and among them is the selection of feedstocks and gasifiers optimal for more efficient and sustainable waste management and use in the production of biogas systems. This review paper identifies the potential application areas in either waste management practices or biogas production and puts forward ways in which AI can be used in these areas. [DOI: 10.1115/1.4066059]

Keywords: sustainable development, artificial intelligence, waste management, biogasification, waste-to-energy, alternative energy sources, energy extraction of energy from its natural resource, energy from biomass, energy systems analysis

1 Introduction

Today we are facing a global waste crisis. Waste generation varies by sector and by region. Clearly, waste management, reduction and disposal, is a big environmental issue that needs to be addressed by citizens, businesses, and government. By 2050, the World Bank predicts that there will be 3.4 billion tonnes of waste generation worldwide. Depending on economic development and consumer habits, waste composition differs by region and nation. The effectiveness of industrial processes, optimizing resource allocation, and enhancing waste management procedures, artificial intelligence (AI) techniques have the potential to assist reduce waste formation. Waste generation in a number of different sectors, like municipal solid waste (MSW) is the most popular sort of waste and often consists of food waste, plastics, paper, and other organic and inorganic elements. Urban India generated about 62 million tonnes of solid garbage waste (450 g/capita/day) in 2015, according to Ref. [1]. Chemicals, scrap metal, electronic waste, and construction debris are just a few examples of the hazardous and nonhazardous waste which can be generated during manufacturing and industrial processes (referred to as industrial waste [2]). Mining (28.1%) and building (34.7%) account for the majority of the garbage. Healthcare facilities [3] produce waste in the form of infectious waste, waste from sharp objects, and noninfectious waste like plastics and paper. Waste must be handled and disposed off carefully since it is very infectious. Electronic waste

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(e-waste) [4] is generated when electronic devices like computers, smartphones, and televisions that also need to be disposed of. According to earlier research, in 2010, India produced 0.4 million tonnes of e-waste; this number may elevate to 0.5–0.6 million tonnes by 2013–2014 [5]. Animal waste, crop residue, and other organic materials are all included in agricultural waste [6], which is produced by farming and agricultural activities. Pollution of the soil and water can result from improper agricultural waste management or disposal. The Ministry of New and Renewable Energy, India, has assessed that forestry and farming remains deposits likely quantify to 120–150 million metric tonnes annually, with a capacity of roughly 18,000 MW [2,7]. Biogas plants go beyond merely producing energy, in contrast to other energy-producing technologies that utilize biomass. They are perfectly suited for using potentially harmful agri-food processing waste and the products that result from post-fermentation that provides valuable natural fertilizer as shown in Fig. 1.

Energy can be generated from waste materials using a series of techniques. The term "waste-to-energy" (WtE) describes a number of technological processes that convert nonrecyclable waste into usable energy sources such as fuels, heat, and electricity. WtE can be generated with the use of a variety of techniques, including landfill gas recovery, anaerobic digestion, gasification, pyrolysis, and incineration. Usage of updraft or downdraft gasifiers, the process of biogasification turns organic waste into biogas, a renewable energy source. Food waste, animal manure, and crop residues are examples of agricultural waste which can be utilized as a feedstock for biogasification. Because of its many benefits like reducing greenhouse gas emissions, waste management, and energy security, biogasification using downdraft gasifiers has gained a lot of attention as an alternative energy source [8]. Biodegradation of organic waste into biogas is done through microorganisms in an anaerobic environment. Biogas is composed of methane, carbon dioxide, and a small amount of other gases. It can be used to heat and power vehicles or for electric power generation [9]. However, the efficiency and success of this process are dependent on several factors such as feedstock composition, process parameters, ambient condition, and design of the downdraft gasifier itself [10]. Biogasification has to be maximized to produce the highest biogas yield and utilize the feedstock optimally.

Now with the use of AI, we can adjust the biogasification settings of the downdraft gasifier to increase productivity, sustainability, and reduce cost. Through biogasification of agricultural waste, we can reduce greenhouse gas emissions, improve waste management, and generate renewable energy. Compared to the traditional approach, AI-based approach offers more accuracy, speed, and data handling. Traditionally the biogasification process is improved by conducting experiments to find the optimal downdraft gasifier operating conditions. It is time and money consuming to do the study and the result may not be applicable to other conditions. But AI-based method analyzes big data by applying the machine learning (ML) algorithm to find the pattern and optimize their performance. According to many studies, the AI-based optimization method outperforms the traditional optimization method when maximizing biogas output from the downdraft gasifier process.

In the process of waste management, including biogasification, AI-based techniques can improve efficiency, alleviate costs, and increase sustainability by optimizing the geometrical and operational parameters of downdraft gasifiers. AI can be integrated into biogasification, gasifier optimization, and waste handling processes in a novel and significant way to develop sustainable waste management systems. There is evidence that AI can increase productivity, decrease waste generation, and increase the production of renewable energy. The importance of research and development in AI techniques in pursuit of environmentally friendly waste disposal methods and attaining sustainable development goals (SDG-5,7) is demonstrated by these benefits.

AI is currently considered one of the major contributors to the enhancement of efficiency and sustainability of waste management systems. This study shows that the integration of AI in several phases of the waste management, which includes waste sorting, route optimization, predictive maintenance, and biogas production from agricultural feedstocks, provided empirical proof of enhancing the process of waste management. In the optimization of the configuration of gasifiers, the usage of AI further proves the potential that AI holds for enhancing energy recovery processes. Contributions highlighted emphasize the positive ways in which AI has transformed the field toward more sustainable waste management practices.

Fig. 1 Various kinds of wastes generated from different sectors

2 Agricultural Wastes Used as Feedstock in Downdraft Gasifier

Agricultural waste can be used as a feedstock for biomass gasification technologies such as downdraft gasifiers [11]. There are some ways that biomass can be converted to a gaseous fuel through downdraft gasifiers [12], which makes it feasible to become heat and/or electricity [13]. Agricultural waste can be classified in a number of ways including crop residues which include the wheat straw (WS) and corn stalks, animal waste, or litter which is dropped by animals, and liquid waste that is produced when food is processed. The types of waste that can be associated with these hazardous wastes are several and comprise those affecting the quality of air and water and are not easy to handle. But by using downdraft gasifiers,stock wastes can be produced as a valuable fuel [14]. Gasification is a process by which the biomass is heated in the absence of oxygen, to generate a synthetic gas referred to as syn gas due to the heat effect on the biomass [15]. There are numerous potential uses for this gas and these uses include using it to power turbines, engines, and turbines as a fuel. In addition to being an environment-friendly, replenishable natural resource, fly ash produced from agricultural waste is ideal for downdraft gasifiers. As a result, agricultural waste can be used as fuel to reduce the amount of waste disposed in landfills, which can have a positive impact on greenhouse gas emissions [16].

Downdraft gasifiers and biogasification are closely related because both provide ways to convert waste into resources. As shown in Table 1, biogasification absorbs these gases and transforms them into a fuel source instead of allowing agricultural waste to naturally decompose, which releases methane and other greenhouse gases into the atmosphere [17–28]. There have been numerous studies looking at biogasification as a means of handling agricultural waste. Biogasification of animal dung, for instance, can

Table 1 Approximate values of biogas, methane, and CO_2 generated from different types of waste in the downdraft gasifier

Types of waste		Biogas (m^3 per tonne of dry matter)	Methane (%)	Carbon dioxide (%)
Animal manure		30–50	60–70	30–40
Crop residues	Wheat straw	60–120	60–70	30–40
	Rice straw	80–160		
	Corn stover	70–130		
Food waste		80–200	50–70	30–40
Energy crops		200–400	50–75	25–50

dramatically reduce greenhouse gas emissions when compared to conventional manure management practices [17,18]. Earlier this year, another study revealed that crop residue biogasification can help reduce environmental effects and be economically beneficial. In Korea, it was found that biogasification of crop residues could produce renewable energy and can reduce greenhouse gas emissions, which can have a positive influence on the environment and the economy as a whole [19]. Based on this analysis, it can be concluded that the biogasification of rice straw and maize straw can provide renewable energy and reduce greenhouse gas emissions. The biogasification of animal manure in China can significantly reduce greenhouse gas emissions as opposed to traditional manure management practices, according to another study [21]. Likewise, biogasification of agricultural waste in India has been found to improve waste management, provide renewable energy, and reduce greenhouse gas emissions [22]. It was found that the biogasification of vegetable and fruit wastes in India could reduce environmental pollution and increase farmer income [23]. Several studies have shown that the biogasification of agricultural wastes like cow manure and rice straw could improve the national waste management practices as well as provide a sustainable energy source in Indonesia [24]. It also highlighted the importance of tower moisture and remain-green traits, which are less discussed in the literature but crucial to cultivar development for dual purposes. For efficient biomass gasification, both industrialized and developing contexts are relevant [25]. Key design factors include gasifier equipment selection and biomass feedstock preparation [26]. Gasification processes are impacted by operating conditions, which were shown to be critical to achieving high efficiencies and optimizing product proportions [27]. The economics of converting waste biomass to power was also examined by comparing waste biomass to purpose-grown biomass [28], using rehabilitated landfill sites as a biomass source.

Rice straw, oil palm fronds, and coconut husks were all identified as having the highest biogas potential in Malaysian research [29]. There was a study performed in the United States that found that corn stover presented a greater potential for biogas generation than cattle manure [30]. Sugarcane bagasse, wheat straw, and rice straw were also compared in India for their biogas potential, with rice straw exhibiting the greatest potential [31]. The highest biogas potential was found among several agricultural residues in Ethiopia [32]. Based on Chinese research, rice straw had the highest biogas yields compared to maize, wheat, and rice straw [33].

Optimization in biogasification processes is considered one of the critical factors on which biogas production and effective use of the feedstock highly rely. These processes have better efficiencies than the conventional ones and hence have become a powerful tool for optimization in the biogasification process. Waste can effectively be managed with the implementation of AI techniques, and it will not only be an improvement to the waste but also generate renewable energy sources and reduce the greenhouse effect of gases. All components of waste management will become precise, efficient, and successful, reducing the cost and enhancing an improvement in environmental outcomes. The sections that follow will continue a description of how AI methodologies further improve operational productivity, precision, and success improvements in waste management processes.

3 Role of Artificial Intelligence in Waste Management Practices

Using AI approaches can make waste management practices easier and more efficient. The collection, processing, transportation, disposal, and monitoring of waste materials are all considered to be part of waste management. The reduction of garbage's negative impacts on the health of general public as well as the environment is the aim of waste management. Converting garbage into energy is one method of waste management. The process of converting trash into useable types of energy, such as electricity, heat, or fuel, includes using technology to do it. Waste can be turned into energy using a number of different processes, such as anaerobic digestion, gasification, and incineration. Reducing the amount of waste that is disposed of in landfills, lowering greenhouse gas emissions, and producing electricity are just a few benefits of turning waste into renewable energy.

AI-based technologies are currently used in nearly all academic disciplines, comprising medicine, linguistics, and engineering, among others, as an output of the development of AI technology and the constraints of conventional computing techniques. The expansion of AI application fields is supported by the modeling techniques used in artificial intelligence's potential to handle noisy, multidimensional data. AI has been universally used in environmental engineering to plan solid waste management (SWM) strategies, simulate soil remediation and groundwater contamination, and solve problems relating to air pollution, simulation of soil remediation, water and wastewater treatment modeling, and ground water contamination [34,35]. Waste management is rapidly using AI to boost sustainability, cut costs, and increase efficiency. Waste management could be transformed by AI by increasing effectiveness, cutting costs, and improving sustainability [36].

By using AI technologies, waste management companies can optimize operations, increase recycling rates, and reduce the

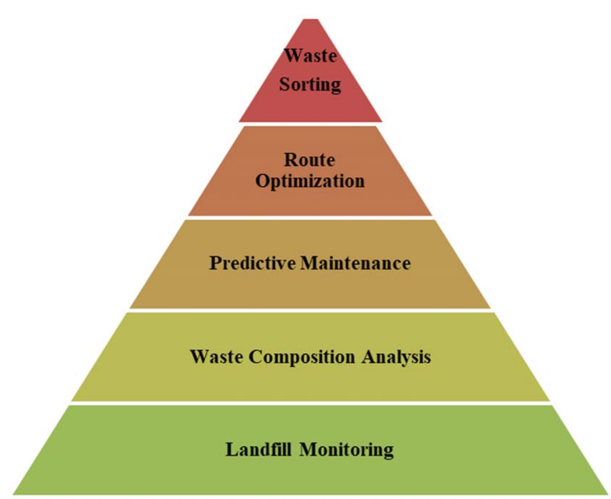

Fig. 2 Different ways AI is being used in waste management

environmental impact of waste disposal [37]. AI helps in the process of waste management in different ways as shown in Fig. 2.

- Waste sorting: Artificial intelligence is used to sort and categorize waste materials such as plastic, metal, and paper. Contrasted to conventional sorting methods, this technology can more accurately identify and separate several types of waste, elevating recycling rates and alleviating waste sent to landfills. Waste sorting facilities and disposal infrastructure serve as filters in the waste management value chain by removing more or less precisely sorted material fractions that can be utilized immediately in production or sold as raw materials on the local or international market, and by alleviating the quantity of waste that must be disposed of in the final stage. Due to this, the division of municipal waste into several categories has received attention in recent decades [38]. Automated/mechanical sorting as well as manual sorting are the two primary technical approaches utilized to separate waste into distinct material streams. Optimization of waste management over a short distance, the system will make use of machine learning and graph theory [39]. An artificial intelligence based hybridized intelligence framework has been developed for the automated optimization of recycling and waste management processes. A digital model that automatically sorts generated garbage and categorizes the type of waste in line with recycling standards is provided in Ref. [39]. It is based on an artificial neural network (ANN) and comprises fusion techniques.
- Route optimization: Artificial intelligence is utilized to optimize waste collection routes, constraining the distance traveled by collection vehicles and minimizing fuel consumption and emissions. With this technology, waste management companies can more efficiently allocate resources by identifying areas with high rates of waste generation. The Harmony Search algorithm is used by an online system that supports e-waste collection for optimization of waste collection vehicles' routes [40]. The waste inputs came from a time series ANN nonlinear autoregressive model, and a waste collection model was developed utilizing a vehicle routing problem network analysis within a geographic information system (GIS) [41].
- Predictive maintenance: Artificial intelligence technologies grew in prominence over time by providing various computer solutions to the intelligent waste problem. AI was effective at managing ill-defined problems, experiences, uncertainties, and incomplete data [42]. ML has great application potential in a field range, comprising waste treatment cycle reduction, waste management decision-making, waste pollution risk alleviation, resource utilization improvements [43]. This is despite

Table 2 AI techniques used in different tasks performed in waste management practices

Task	Technique	Dataset	Accuracy (%)	Result obtained	Reference
Waste sorting	ANN	Google images and Flickr material database (2400 images)	91.7	Digital-enabled circular economy vision could improve the waste sorting services	[38]
	CNN	2400 input image data were obtained from a plastic detection model library in GitHub	97.5	Provide accurate waste classification	[49]
	SVM	–	93.4	SVM outperformed in terms of accuracy	[50]
	Random forest	–	95.8	Good performance in identifying different types of waste	[51]
	Deep belief networks	3000 garbage images, with 500 images per class	93.8	System achieved precision of 91.2% and a recall of 90.9%	[52]
Route optimization	Harmony search algorithm	–	–	Waste collection = higher 5.1–13.2%. Total mass of collected waste appliances up to 7%.	[40]
	ANN with GIS	Austin's Open Data Portal	–	Dual-compartment truck model can save 10.3–16.0% of total travel distance	[41]
	TS	Solomon's Vehicle Routing Problem with Time Windows benchmark instances	95.2	Tabu Search algorithm is shown to be more robust	[53]
	GA	Real-world data collected from the city's waste management system (Medina, Saudi Arabia)	92.24	Average reduction of 18.68% in the travel distance and a 19.62% reduction in the travel time	[54]
	ACO	Real-world data obtained from the waste management company (Rabat, Morocco)	93.5	27.8% reduction in the distance traveled and a 34.5% reduction in the travel time	[55]
	ANN	Real-world data collected from the city's waste management system (Sao Paulo, Brazil)	93.8	15.4% reduction in the distance traveled and a 16.5% reduction in the time	[56]
Predictive maintenance	ML + NN model	200 images from five different forms	92.53	MAE of 0.55% and MSE of 0.08%	[42]
	(IoT-SWM) model with random forest algorithm	Real-time environment from the sensory readings (510 instances)	95.8	Waste collection efficiency of 94.2%, 20% reduction in the carbon footprint, reduction in the number of collection trips by 31.8%	[44]
	RF	Real-world data from 31 solid waste collection vehicles over a period of six months	92.56	Reduction in maintenance costs by 12.5%	[57]
	CNN	Real-world data from 54 garbage trucks over a period of six months	98.6	Reduction in maintenance costs by 25%.	[58]
	LSTM	Real-world data from 25 solid waste collection vehicles over a period of three months	91.7	Reduction in maintenance costs by 17%	[59]
	SVM	Real-world data from 42 garbage trucks over a period of six months (Banglore, India)	92.6	Reduction in maintenance costs by 20%.	[60]

its constraints of low interpretability, inadequate data, and unclear model selection principles. A sustainable and intelligent ecosystem must have efficient waste management. Improper waste management in the neighborhood increases the chance of contagious diseases spreading quickly. Traditional waste object management is more labor-intensive, time-consuming, and relatively ineffective. Mishra et al. [44] demonstrate the development of an intelligent of things enabled smart waste management (IoT-SWM) model with predictive capabilities.
- Waste composition analysis: AI is utilized for analyzing the waste composition, revealing insights on the sources and categories of waste generated in a specific area. Develop programs for trash reduction and recycling that are specifically targeted at using this information. Waste composition analysis has the potential to be considerably improved by AI, making it more rapid, accurate, and economical. A sample's materials can be determined by spectroscopic data interpretation and AI. This technique is absolutely helpful for assessing hazardous waste, which calls to be handled and disposed of carefully [45,46]. The artificial intelligence application can be used for waste composition analysis, including data mining, spectroscopy, and image recognition [47]. The benefits of employing AI for waste analysis, like improved accuracy, speed, and efficiency, are described.
- Landfill monitoring: AI is used to monitor landfill activities, including waste disposal and landfill gas emissions. This technology is helpful to operators as they can spot potential environmental and safety issues and take the necessary precautions to avoid accidents with the help of this technology [48].

According to the study given above, AI approaches have shown positive outcomes in waste sorting with high accuracy rates. The quality and quantity of the training data set will have an impact on the accuracy rates, and should be emphasized. The efficiency of these techniques may also be influenced by particular waste sorting applications and the specific classification features. Using AI techniques such as genetic algorithm (GA), ant colony optimization (ACO), Tabu Search (TS), and ANN, waste collection routes can be effectively optimized. These algorithms' accuracy percentages ranged from 92.24% to 95.2%. In addition, there was a 15.4–27.8% alleviation in travel time and distance as shown in Table 2. It is possible to accurately predict the maintenance needs of waste management equipment using AI techniques such as random forest (RF), convolutional neural network (CNN), long short-term memory (LSTM), and support vector machine (SVM). These algorithms' accuracy percentages ranged from 91.7% to 98.6%. In addition, maintenance expenditures were alleviated by 12.5–25%.

AI methods could elevate the efficiency as well as the efficacy of waste management practices, alleviating the detrimental effects of waste on public health as well as the environment. Yet it is essential to make sure that waste management AI applications are developed in a responsible and ethical manner, taking into account any potential risks and uncertain consequences. By creating predictive models, employing optimization algorithms, examining sensor data, and real-time regulating the process, AI approaches can be utilized for improving the parameters of energy generation from waste. The efficacy of the waste-to-energy process can be improvised, and the environmental impact of waste can be alleviated, by using AI techniques.

In 2019, over 1.8 billion metric tonnes of MSW were generated globally, and 140 Terawatt-hours (TWh) of energy were reportedly produced from MSW, as per the International Energy Agency (IEA) [61]. About 2% of the globe's electricity is generated in this way. The IEA also points out that WtE technologies have been implemented by more than 40 nations globally, with Europe leading the way in terms of WtE. A WtE contributes a large part of the electricity generation in several European countries including Sweden, Norway, and Switzerland [49]. It is substantial to note, nevertheless, that different countries and regions use waste in various ways when it comes to energy generation. For instance, a sizeable portion of waste in low-income nations is not collected, let alone utilized for producing energy. The adoption of WtE technologies has also generated discussion because of the negative effects they have on the environment. Although WtE can be a source of renewable energy, it also generates pollutants such as carbon dioxide and nitrogen oxides which can worsen air pollution and climate change. Consequently, before looking at WtE as a solution, waste reduction and recycling should be prioritized as the first line of action.

4 Artificial Intelligence Optimization for Enhancing Biogasification Process in Downdraft Gasifies

The biogasification process, which involves the organic material's anaerobic digestion for biogas production—a renewable source of energy useful for heating, power generation, and transportation—can be effectively utilized with AI-based optimization. Machine learning algorithms are utilized in the biogasification process's utility of AI-based optimization to analyze data collected from multiple sources, including sensors. As a result, operators may optimize the process parameters to maximize biogas output and alleviate operating costs. These algorithms can detect patterns and predict fluctuations in the process. The potential advantages of AI-based optimization in the biogasification process, notably in gasifiers, have been shown in numerous research studies as shown in Fig. 3.Various crucial areas can benefit from the application of AI-based optimization in biogasification to boost efficiency and productivity.

4.1 Feedstock Selection and Pre-treatment. Based on variables including availability, cost, and energy content, AI can assist in choosing the best feedstock for gasification. To increase the effectiveness of gasification, AI can also optimize the pre-treatment of the feedstock, such as drying or grinding. There are several interesting examples of AI-based feedstock selection and pre-treatment for biogasification through gasifiers.

Downdraft gasification technology has utilized various AI techniques to select appropriate feedstocks like rice straw, corn stover, and wheat straw for biogasification, yielding different levels of accuracy and efficiency as shown in Table 3. The selection of the AI technique is contingent upon the available data set and the

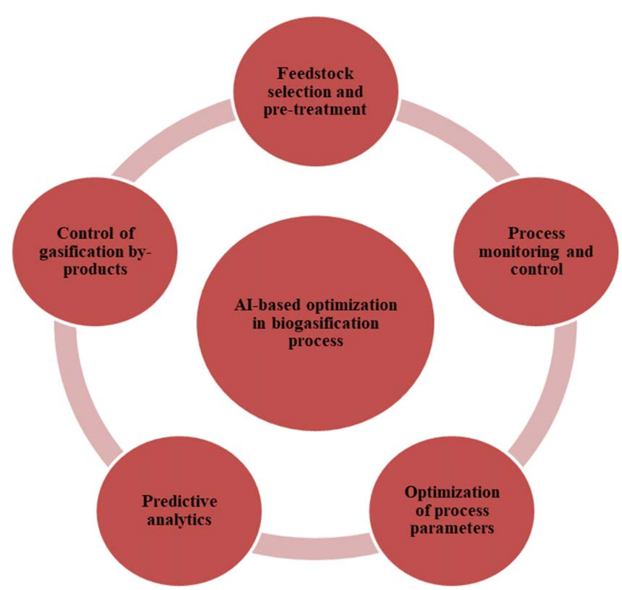

Fig. 3 AI techniques used in different areas in the process of biogasification

Table 3 AI-based optimization techniques for selecting wheat straw, rice straw, and corn stover as feedstock for the biogasification process in downdraft gasifiers

Feedstock	AI technique	Methodology	RMSE	MAE	Accuracy	Efficiency	Reference
Corn stover	ANNs	–	1.76	1.46	95.7	98.6	[62]
	SVMs	–	0.103	0.074	97.5	–	[63]
	RF	–	–	–	97.5	88.9	[46]
	DTs	–	44.8	34.9.	85.6	–	[64]
Rice straw	ANN	–	0.0025	0.0021	97.8	98.4	[65]
	SVM				97.8	84.5	[44]
	SVMs	–	0.0098	0.0078.	96.3	–	[66]
	RF	–	25.67	19.67	91.5	–	[67]
	CNN	–	0.0075	0.0061	92.5	–	[68]
Wheat straw	Artificial neural network	Multi-layer perceptron with backpropagation algorithm	–	–	91.3	87.2	[43]
	Artificial neural networks	ANN model with a backpropagation algorithm	–	–	92	Satisfactory	[69]
	SVM	SVM model with a radial basis function kernel	–	–	90	Satisfactory	[70]
	DTs	DT model with a C4.5 algorithm	–	–	88	Satisfactory	[71]

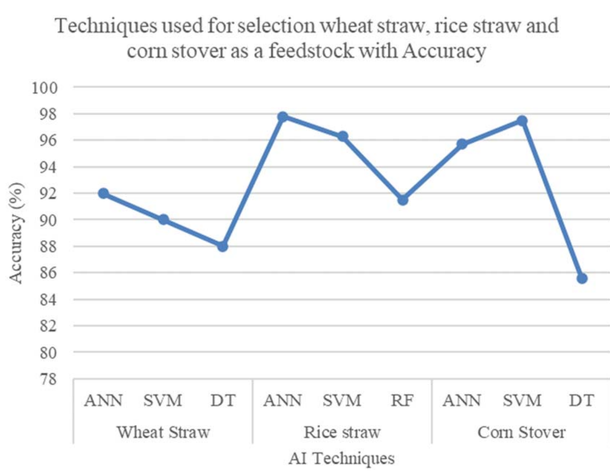

Fig. 4 Different techniques used for the selection of wheat straw, rice straw, and corn stover as a feedstock with accuracy

specific needs of the application. Performance assessment metrics for the models comprise of root mean squared error (RMSE) and mean absolute error (MAE).

AI techniques can be highly useful for accurately selecting feedstock. In contrast to decision trees (DTs) and random forest, the graph above shows how correctly ANN and SVM techniques optimize the values. Data evaluation a lot of data about diverse feedstocks and their attributes can be analyzed by AI. AI can find patterns and relationships in these data that may not be visible to humans. This may make it easier to choose feedstock with the necessary characteristics. To estimate the characteristics of novel feedstocks, AI can create predictive models based on past data. Even before it is tested, this can assist in choosing the feedstock with the appropriate qualities. This can evaluate feedstock photos and determine the qualities of the materials. AI, for instance, may examine biomass image data to identify its composition and quality as shown in Fig. 4. To find pertinent details about feedstocks, such as their characteristics, accessibility, and cost, evaluate text data as well. This can aid in choosing feedstock that satisfies the required standards. Overall, AI can aid in accurate feedstock selection through data analysis, predictive model building, image analysis, and natural language processing. AI can make the process of choosing feedstocks more effective, accurate, and economical as shown in Table 4.

4.2 Process Monitoring and Control. AI may be used to continuously monitor and control the temperature, pressure, and gas composition during the gasification process. Two types of classifiers have been given in Ref. [77] for the prediction of producer gas composition as well as its calorific value achieved through woody biomass gasification in a downdraft gasifier: binary least squares support vector machine and multi-class random forests classifiers. This can aid in process optimization and early problem detection as shown in Fig. 5. Using ten-fold cross-validation, the proposed techniques were created and tested on 5237 data samples, with binary and multi-class classifiers achieving prediction accuracy values over 96% and 89%, respectively. Chemical looping gasification (CLG), a cutting-edge gasification method, allows solid hydrocarbon feedstocks to be converted into a nitrogen-free,

Table 4 Optimized AI techniques for selecting wheat straw, rice straw, and corn stover as feedstock for the biogasification process with higher accuracy and efficiency

References	[72]	[73]	[74]	[75]	[76]
Feedstock	Wheat straw	Rice straw	Rice husk	Corn stover	Soybean residue
AI technique	Artificial neural network	Support vector machine	Decision tree	Random forest	Bayesian network
Accuracy (%)	92	97.8	86.7	97.5	90.8
Efficiency (%)	87.2	84.5	82.1	88.9	86.7
Evaluation metrics	Root mean square error (RMSE), coefficient of determination (R^2), and correlation coefficient (r)	MAE, RMSE, R^2	Specificity, sensitivity, area, accuracy, under the receiver operating characteristic curve (AUC-ROC)	Accuracy, precision, recall, F1-score, AUC-ROC	Accuracy, specificity, sensitivity, AUC-ROC

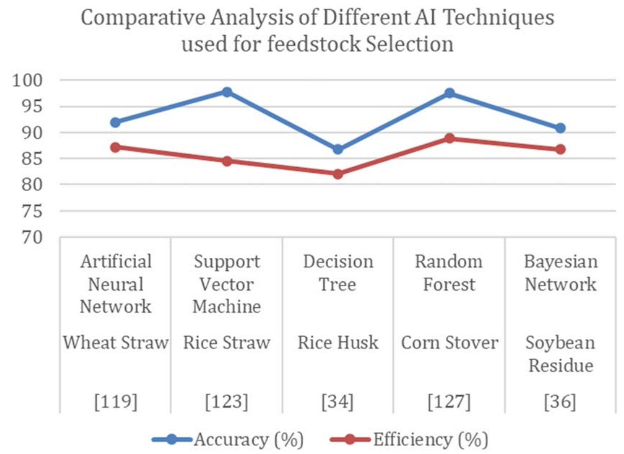

Fig. 5 Comparative assessment of accuracy and efficiency of AI techniques for feedstock selection in downdraft gasification

high-calorific synthesis gas without the utilization of an expensive air separation unit [78]. Dieringer et al. [78] offer two methods to achieve autothermal CLG behavior that are based on simulations of equilibrium-based processes. Dilution of active oxygen carrier materials with inert heat carriers has been considered as a first step for alleviating oxygen availability in the fuel reactor. The suitability of regulating the airflow to the air reactor was also examined to regulate the oxygen availability in the fuel reactor. Based successfully on the experimental data of the plant, a static model for the gasifier has been constructed in Ref. [79], and this could be utilized to adjust the fuzzy logic controller. The gasifier system's implementation results are discovered to be superior to those of traditional control and computer-based measurement. The temperature is controlled via fuzzy control, which alleviates overshoot and settling time.

4.3 Optimization of Process Parameters. The term "optimization of process parameters" refers to the modification of various variables that have an impact on the biogas production process in order to maximize efficiency and output. In order to produce biogas, which is mostly made up of methane and carbon dioxide, organic materials like agricultural waste, sewage sludge, and food waste must be broken down in the absence of oxygen. Temperature, pH, retention duration, substrate loading rate, and mixing intensity are a few process variables that can be improved to increase biogas production. The performance of the biogasification process can be impacted by each of these variables, and optimization is identifying the appropriate values for each parameter to achieve the best possible biogas production. For instance, an optimal temperature for biogas manufacture is usually in the region of 35–40 °C, and operational temperature alterations in the bioreactor negatively impact the process. Similarly, it is very crucial to regulate the pH balance within the range that is 6 s and this is so very important 5–7. It is also necessary to consider the fifth fact which is highly useful for the microorganisms in the reactor. Other vital aspects involve the selection of proper substrates, proper selection of inoculants through which favorable microbes can be introduced inside the reactor, and moderate to high mixing levels so that substrates, nutrients, etc. get well mixed inside the bioreactor. The use of AI can improve several factors that affect the syngas production and quality, such as the ratio of feed to air, temperature, and retention time. For instance, ANNs were used to enhance the process parameters of the two-stage anaerobic digestion process of food waste study as a way of improving the biogas production [80]. In this case, the GAs were employed to dial-in the process parameters for yield of biogas through digestion of food waste as well as from pigs' waste [81]. Furthermore, particle swarm optimization (PSO) has been used to optimize the process parameters within a two-phase anaerobic digestion process for rice straw [82]. Finally, an application of SVMs for improving the process parameters of a two-step anaerobic digestion of the corn stover was examined [83].

4.4 Predictive Analysis. A predictive analysis involves using mathematical and statistical models to predict how the biogasification process will progress. Methane and carbon dioxide are the primary components of biogas, which are produced by the biological process biogasification. The effectiveness of the biogasification process can be better understood using models that utilize predictive analysis [84]. These models can consider variables such as temperature, pH, substrate composition, and microbial communities. This can be followed by the application of these models to process optimization as well as scenario prediction using these models. Biogas production can be optimized using predictive analysis, for instance, by optimizing the substrate mix or by predicting how environmental changes would affect biogas production [85]. Biogasification can benefit from predictive analysis in terms of efficiency and sustainability, which can help with the transition to a more sustainable energy system and perhaps reduce greenhouse gas emissions. A machine learning algorithm can be used to forecast the yield and quality of syngas and adjust the process accordingly [86]. Biogasification requires predictive analysis to maximize efficiency and ensure biogas production. In biogasification processes, ANNs, SVMs [84–87], deep learning [87], and fuzzy logic are some of the AI approaches employed for predictive analysis.

4.5 Control of Gasification Byproducts. Some of the byproducts include ash and tar and these may influence gasification efficiency and its effects on the environment would be more manageable with the help of artificial intelligence. By implementation of different AI techniques, the parameters in biogasification byproducts can be regulated effectively. It identifies that ANNs could utilize data-driven learning to predict the optimum control parameters for a specific biogasification process [88]. Indeed, fuzzy logic encompasses data imprecision and uncertainty and provides the best control settings [89]. Since GAs provide a population of potential solutions, which comes from the concept of niching, they can seek for the proper control parameters [90]. Considering this, PSO has been used in several research studies to enhance the control of the parameters associated with the byproducts of gasification in the biogasification process [91].

5 Maximizing Biogas Production From Downdraft Gasified: Optimization of Operational Parameters

The agricultural waste in case of going through this process comes out to produce the nutrient and at the same time the biogas which is a source of energy. Another type of agricultural waste is crop residues. These can also be used to a large extent in manufacturing biogas. Crop residues can be transformed into biogas. Due to the incentives that arise from it, which include the availability of renewable energy sources, efficiency in waste disposal and management, improvement of soil productivity, and having little effect on the economy, the biogas production from animal waste has a significant contribution to climate change [92]. It indicates that the congestion occurring during these hours has a negative impact on children, [93]. Some of the existing renewable energy sources include electricity as well as calibrated heat to warm homes and cook utilizing biogas foods preparations or biogas stoves. At the same time, it could positively influence energy security, potentially decreasing dependence on fossil fuels and reducing green house gas (GHG) emissions for the production of biogas from agriculture [92,94,95]. This is a problem because, if such wastes can be used in a way that makes them a part of a product that is worth something, it would go a long way in helping to solve the issue of waste disposal. I came to know that it can reduce the rate of waste that is being dumped on the dumps/or recycle the wastes and it can also eliminate the pollution of the environment [96–99]. Also, improve soil fertility. The digestate produced during the biogasification process can be utilized as a fertilizer, which comprises valuable nutrients that can enhance crop productivity and soil quality [99,100]. Farmers and rural communities benefit economically from this. It can lower the cost of energy inputs and fertilizer inputs while earning money from the sale of biogas [101–104]. By lowering greenhouse gas emissions, biogas generation from agricultural waste can aid in the mitigation of climate change. Methane, a strong greenhouse gas, is produced by the biogasification process. Although methane can be caught and used as a renewable energy source, doing so will result in a decrease in the amount of methane and other greenhouse gases that are released during agriculture [93,98–108]. The feedstock-to-air ratio, temperature, and residence time are just a few of the process variables that have a significant impact on how efficiently biogas is produced. To produce the most biogas, these variables must be tuned. In this section, different case studies were discussed which are AI based and are utilized for the optimization of these parameters for biogas production from various crop residues.

A 10-L working volume anaerobic digester was used for the experiment in Ref. [61] with wheat straw as a feedstock. GA, a type of artificial intelligence optimization technique, was used to optimize the process parameters. A MATLAB program was used to incorporate GA. The maximum output of the biogas was the objective to maximize the optimization. Biogas output was optimized by varying the feedstock-to-air ratio (2–10), temperature (30–60 °C), and residence time within these ranges (10–30 days). It was observed in the findings that maximum biogas production was achieved using a feedstock-to-air ratio of 6, a temperature of 50 °C, and a 20-day residence time. The maximum biogas production reached 0.85 L/g VS (volatile solids) added under these optimal conditions, representing a 42% increase in biogas production than that produced in the initial biogas production under unoptimized conditions. The study quoted in Ref. [109] used the response surface methodology (RSM) technique to maximize biogas production from rice straw. The RSM is a very effective statistical methodology that describes the relationship between the independent and dependent variables and is used to optimize the process parameters. The laboratory-scale anaerobic digester was used to operate this experiment for 30 days at 35 °C. In these conditions, biogas production was 0.65 m^3/kg VS with an initial biogas output of 0.39 m^3/kg VS at 35 °C, pH of 7.2, retention time of 25 days, and feedstock composition of 60% rice straw and 40% cow dung. The results indicate that this temperature, pH, retention time, and feedstock composition are most favorable for biogas production from rice straw. Production compared to production with the first settings resulted in higher production (0.39 m^3/kg VS).

Biogas production predicted by the RSM model showed a high coefficient of determination ($R^2 = 0.989$). Corn stover is one of the various agricultural wastes across the globe and has much potential for use as a feedstock in biogas production. However, biodegradability is low, and it contains a high lignocellulose amount, both undesirable for being easily digestible. The AI techniques have been utilized to optimize the biogasification process after facing constraints to overcome the problems [110]. Results showed that the optimum parameters for the production of biogas are an *F*/*I* ratio of 2.2, pH 7.4, temperature at 36.4 °C, and high retention time (HRT) of 21.7 days. Using these process variables, the ANN model was able to predict the biogas output with an R^2 value of 0.98. For comparison with the initial conditions, the optimal conditions showed biogas production that amounts to 237.4 mL/g VS added. The optimization of the process parameters was carried out using artificial neural networks and the response surface methodology in the study. The RSM was employed for designing the experiments along with model development, while ANN was applied to predict and optimize the process parameters [111,112]. Soybean cultivation residue, known as soybean residue, is widely available in most countries. Biogas produced from residue soybeans can benefit the environment and generate green/renewable energy. Unfortunately, the ideal process parameters for generating biogas from soybean residue are less well known. This study applies an artificial neural network model to optimize the biogas-generating process [113]. The optimized process parameters for biogas generation through soybean residue using the ANN model were 9.26% TS contents, a pH of 7.4, a temperature of 37.8 °C, and a retention time of 22.5 days. Under these scenarios, the actual biogas production rate was 0.36 L/g VS. Soybean residue and corn stover were optimized for biogas production in a downdraft gasifier using different AI techniques. The highest biogas production of 0.85 L/g was found in wheat straw after the operational parameters were optimized using GA. Soybean residue produced 0.36 L/g where the same set of parameters was optimized using ANN. Corn stover was considered to be relatively less efficient for biogas production using ANN techniques, where 0.2374 L/g was produced. Overall, it can be concluded that AI techniques can be exploited to optimize operational parameters for enhanced biogas production from various kinds of feedstocks in a downdraft gasifier.

The primary and secondary air flowrates, along with the height and throat of a downdraft gasifier, also contribute to the performance of a downdraft gasifier. The primary air flowrate means the amount of air introduced in the gasifier at the bottom of the reactor to initiate the combustion process. Generally, the primary air flowrate is controlled to fix the temperature in the gasifier and to complete the conversion of biomass totally into the gas. The secondary air flowrate means the amount of air introduced to the gasifier above the combustion zone. The secondary air provides the exhaust combustion and ensures that the gas produced is high quality. The secondary air supply rate is frequently controlled to ensure that the right oxygen at the gasifier is maintained. Otherwise, its purity can affect the energy content and the composition of the gas produced. The gas height set determines the time the biomass is against the gasifier residence, and therefore, it affects the degree of gasification. Conversely, the diameter of the throat is tailored to control the gasification air velocity and the feedstock velocity. It is necessary to note that most researchers have achieved maximum optimization of gasification and increased biogas production through proper annulation of the set parameter of throat diameter and feedstock height, through demand control of the air supply rates by attending to the feedstock property, moisture content, and the gasification temperature.

6 Optimizing Geometrical Parameters of Downdraft Gasified Using Artificial Intelligence Techniques

The design of gasifier for maximum biogas production is crucial for efficient biogas production from agricultural waste [91,114–120]. AI techniques have been used to design gasifiers and several comparative studies have been done to evaluate the performance of these techniques. In a comparative study of four AI techniques (ANN, SVM, GA, and PSO) for designing a downdraft gasifier, GA was found to be the best. The optimized values for GA were primary air flowrate 0.024 kg/s, secondary air flowrate 0.021 kg/s, and throat diameter 0.059 m [114]. Another study compared the performance of three AI techniques (GA, PSO, and Artificial Bee Colony Algorithm (ABC)) for designing an updraft gasifier. The results showed that GA was the best and the optimized values were primary air flowrate 0.004 kg/s, secondary air flowrate 0.007 kg/s, and bed height 0.25 m [115].

In a study, three AI techniques including GA, PSO, and differential evolution were applied and compared based on their ability to enhance design of a fluidized bed gasifier. The findings demonstrated that the GA technique was the most effective, and the optimized values obtained were a primary air flowrate of 0.008 kg/s, secondary air flowrate 0.012 kg/s, and the bed height of 0.4 m [116]. A current study compared the performance of three AI techniques (ANN, GA, and PSO) for optimizing an updraft gasifier design. The results showed that the GA technique was the most effective, and the optimized values obtained were flowrate of primary air was 0.006 kg/s, flowrate of secondary air was 0.007 kg/s, and bed height of 200 mm [117]. In Ref. [118], the Taguchi method was employed to determine the optimal design of a gasifier for maximum biogas yield. The maximum combustion efficiency of the designed furnace was achieved by selecting the flowrate of primary and secondary air as 0.022 m^3/min and 0.015 m^3/min with a bed height of 20 cm and a throat diameter of 6 cm. Thus, biogas production was raised to 22.6% compared with the initial design of the plant.

The two design parameters that are important in downdraft gasifiers are the bed height and throat diameter. Bed height is the height of the biomass bed in the gasifier being considered. More often, the bed height's measurement is made from the nozzle plate's top surface to the bed's top surface. The bed height is a significant parameter because it affects the residence time of biomass in the gasifier and gas produced quality. A taller height of the bed can increase the residence time and improve the quality of gas but can also increase the pressure drop along with an increased energy requirement to maintain proper gasification. Throat diameter refers to the diameter of the throat section in the gasifier—the section within which the gasification reaction occurs. Throat diameter is a substantial parameter since it affects gas velocity and gas quality.

While an increase in throat diameter may improve gas velocity and hence gas quality, it may also decrease the residence time and elevate the possibility of incomplete combustion. In the design of a downdraft gasifier, as in Fig. 6, the required quality of gas, type of biomass fed, and other operating parameters such as temperatures, pressure, and gas flowrate are usually considered in determining the bed height and throat diameter. The bed height and throat diameter size must be properly designed in order to ensure proper gasification and consistent gas quality. The air is broken down into the primary air and the secondary air when being used to cause the conversion of biomass into a gas which may then be used for energy. The primary air flowrate provides oxygen to meet the requirements of the gasification reaction. A decrease in this rate can result in incomplete combustion and decreased efficiency, while an increase in this rate can lead to excess air and reduced efficiency of gasification. Mean-reduced and secondary flow provides the appropriate quantity of air essential to maintain the temperature of the gasification reaction. Meanwhile, the secondary air flowrate maintains the temperature of the gasifier gasification and, thus, increasing the rate helps in efficiency maximization while at the same time, increasing ash and tar in the gas. It may lead to clogging and other operational problems. Primary and secondary air flowrates in downdraft gasifiers are usually controlled manually or by automation systems that monitor and adjust air flow based on gasifier temperature, pressure, and other operating parameters. The amount and control are affected in such a way as to enable efficient gasification and consistent quality of gas.

An artificial neural network was used to optimize the design of a gasifier for maximum biogas production. The optimized values of primary and secondary air flowrates, bed height, and throat diameter are 0.036 m^3/min, 0.018 m^3/min, 24 cm, and 4 cm, respectively. The biogas production increased by 33.8% compared to the initial design [119]. GA was utilized for the optimization of the gasifier design for maximum biogas production. The optimized values of primary and secondary air flowrates, bed height, and throat diameter were found to be 0.031 m^3/min, 0.015 m^3/min, 21 cm, and 5 cm, respectively. The biogas production was increased by 37.5% compared to the initial design [120]. The study conducted in Ref. [91] shows that the PSO algorithm was used for optimizing the design of a gasifier for maximum biogas production. The optimized values of primary and secondary air flowrates, bed height, and throat diameter were found to be 0.025 m^3/min, 0.017 m^3/min, 22 cm, and 5 cm, respectively. The biogas production was increased by 29.5% compared to the initial design [91].

In Fig. 7, it has been proved that biomass has shown its potential as a substitute for fossil fuels. Gasification through a downdraft gasifier is a suitable thermochemical method for recovering energy from waste products such as agricultural wastes. Several biomass fuels, including eucalyptus wood (EW), rice straw, bamboo wood (BW), WS, and coconut shell, have been used to test the gasifier's performance (Corn Stover). When the same feed rate (=20 kg/h) and equivalence ratio (=2.8) as in the base scenario are established for all the feedstocks, there will be fluctuations in the char flowrate throughout the gasifier reduction zone for the biomass resources. The biomass's content and the pace of reduction processes affect the char flow. It has been discovered that the char conversions of EW, BW, WS, and CS are finished well before the reduction zone described in Ref. [121]. By combining a process model with data analysis tools, the author of Ref. [122] suggests a practical way to forecast and optimize the production of syngas three varied types of agricultural waste from Northeast China and 56 distinct biomasses were utilized as the gasification feedstock for the examination of the effects of operation parameters and biomass compositions on the production of syngas. A verified Aspen Plus process model was utilized for the biomass gasification procedure and the techno-economic analysis. The findings of the sensitivity analysis showed that a lower temperature (about 600 °C) and a lower steam-to-biomass ratio (S/B) were the best operating parameters for generating a higher lower heating value of syngas (around 0.1). With the use of two biomass fuels, several cleaning devices, including cyclone separators, wet scrubbers, biomass filters, and auxiliary filters, were evaluated for performance [123]. According

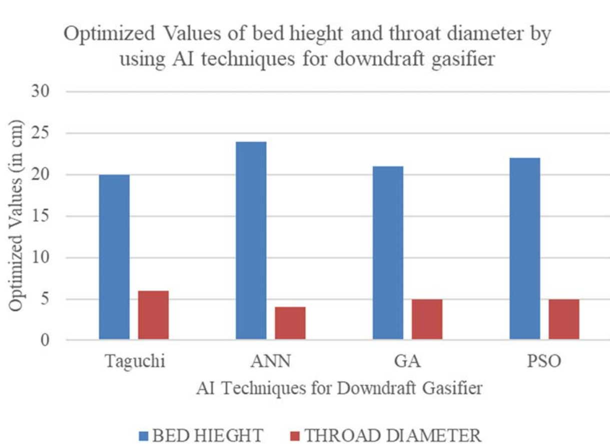

Fig. 6 Optimized values of bed height and throat diameter using AI techniques for the downdraft gasifier

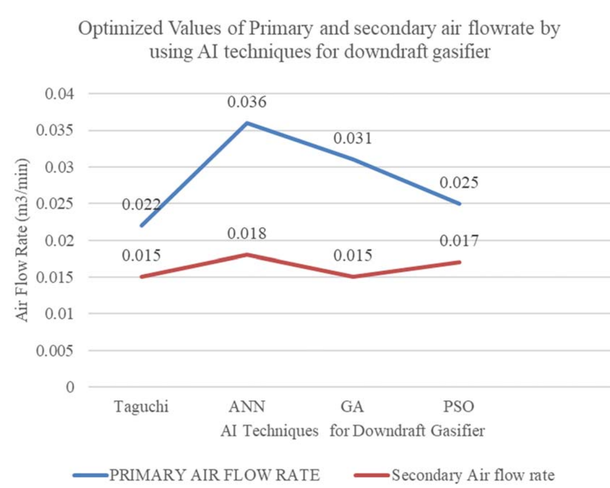

Fig. 7 Optimized values of primary and secondary air flowrates using AI techniques for the downdraft gasifier

Table 5 Optimized operational parameters for biogas production in downdraft gasifier

AI technique	Feedstock	R^2 value	$F:A$	Temperature (°C)	Retention time (days)	Biogas produced (L/G)	Result	References
GA	Wheat straw	–	6	50	20	0.85	Biogas production was 42% higher when compared to the unoptimized condition	[102]
AI-based response surface methodology	Rice straw	0.989	–	35	25	0.65	Biogas production was higher	[103]
ANN	Corn stover	0.98	2.2	36.4	21.7	0.2374	71% increase in biogas production	[104]
GA, support vector regression, and ANN	Rice husk	–	–	55	–	–	42% increase in biogas production	[105–107]
ANN	Soyabean residue			37.8	22.5	0.36	50% increase in biogas production	[93]

Table 6 Application of AI techniques for downdraft gasifier for prediction of syngas and an increase in gasification efficiency

Study	AI techniques used	Gasification efficiency (%)	Syngas production (N m^3/kg)	Feedstock	Gasifying agent
[124]	Support vector machine, artificial neural network	89.19	1.82	Rice husk	Air
[125]	Artificial neural network, Radial basis function (RBF) networks	82.30	1.6	Wood	Air
[126]	Artificial neural network, GA	86.60	1.75	Rice husk	Steam
[127]	Artificial neural network, PCA, partial least squares	92.10	1.9	Corn cob	Air
[128]	LSTM	91.80	1.86	Sugarcane	Oxygen
[124]	Artificial neural network, GA	90.27	1.8	Corn stover	Air
[129]	Convolution neural network, SVM	85.31	1.68	Wood pellets	Oxygen

to the study's findings, before cleaning the biomass reactor, wood chips produced 6600 mg/N m^3 less tar than corn cobs (7500 mg/N m^3). The tar concentration in wood chips decreased from 6600 to 112 mg/N m^3 after going through the entire cleaning procedure, whereas it decreased in maize cobs from 7500 to 220 mg/N m^3. The relative overall tar removal efficiencies for the cyclone separator, wet scrubber, biomass filter, and auxiliary filter were observed as 72%, 63%, 74%, and 35%, respectively (Table 5).

Technological integration with gasification will lead to a better understanding of environmental, economic, and social impacts. In recent years, thermodynamic equilibrium and computational fluid dynamics models have been widely used for this purpose. But still, it needs more optimal understanding. For this, the use of AI like ML models can be considered as an alternative for effective mapping of nonlinear input–output relationship and to prove its potential over conventional approaches. Recently, ML has attracted the attention of researchers to design more efficient predictive tool for optimal thermochemical processes. A prediction model will result in better waste-to-energy prediction and data-driven optimization models will result in the enhancement of gasifiers' performance with optimal parameter selection. Some of the major research contributions of AI/ML are presented in Table 6.

The studies given above explored the prediction of gasification performance and parameters in downdraft gasifiers using machine learning techniques and artificial intelligence. Specifically, SVMs, GAs, ANNs, and principal component analysis (PCA) have been used to model and optimize gasification efficiency, gas composition, and process parameters for various biomass feedstocks. These studies primarily focused on downdraft gasifiers, which are commonly used for biomass gasification. These gasifiers function by allowing the biomass to flow downward through a reactor, and at the same time, air or oxygen is provided from below. This leads to a combustion zone in which the biomass is converted to gas, and thereafter, it goes into the reduction zone where the gas is reduced to form a clean fuel called syngas. The researchers concluded that it is possible to enhance gasification efficiency together with an accurate prediction of gas composition while using machine learning models like ANN, SVM, and GAs. PCA has been proven to be a tool used in reducing the input variables in the process of modeling. LSTM neural networks, as well as CNNs, have also been applied in the modeling of the gasification parameters from different feedstocks, and interesting results have also been obtained.

Overall, these studies do signify the ability of machine learning techniques as well as artificial intelligence in improving better efficiency and performance of biomass gasification in downdraft gasifiers, which could further help in the development of sustainable-based energy systems. The artificial neural network model's application in operational environment prediction ANN is best suited for downdraft gasifiers, as shown in Fig. 8. It will be helpful in predicting the capacity of downdraft for power generation. Increasing the gasification efficiency of a downdraft gasifier

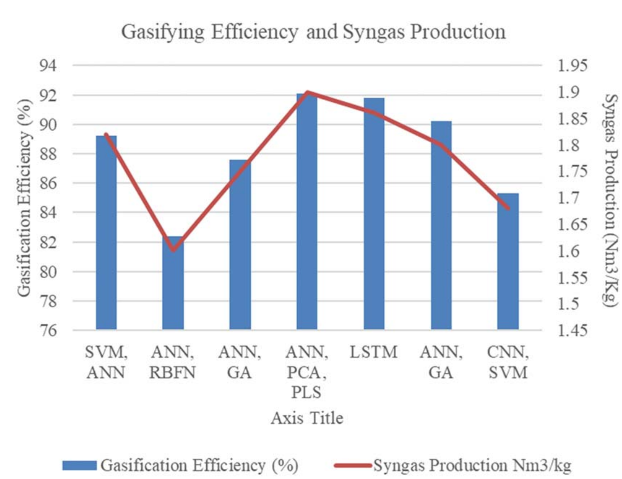

Fig. 8 Increase in gasification efficiency and prediction of syngas production after applying AI techniques

requires a comprehensive approach that considers all aspects of the gasification process, from feedstock preparation to gas cleaning. Proper control of air flow, bed height, throat diameter, feedstock preparation, preheating, heat recovery, and syngas cleaning can lead to significant improvements in gasification efficiency. The AI techniques application in the biogasification process can lead to an increase in gasification efficiency by optimizing the feedstock selection, process parameters, gasifying agent, and prediction of syngas production.

7 Conclusion

Effective waste management systems are crucial for sustainable development as waste generation remains a significant global issue. AI is increasingly being utilized to optimize waste management practices such as waste sorting, route optimization, and predictive maintenance. Maximum accuracy rates of 95.8%, 95.2%, and 98.6% were achieved using random forest for waste sorting, Tabu search for route optimization, and CNN for predictive maintenance, respectively, highlighting the importance of AI in waste management practices. Additionally, AI techniques such as SVM and ANN can assist in selecting appropriate feedstocks for biogas production from different agricultural crops, like rice straw, wheat straw, and corn stover. Optimizing the biogasification process with AI increased biogas production from agricultural crops by approximately 40% compared to unoptimized conditions, indicating the effectiveness of AI in this field.

Furthermore, gasifier design optimization using AI techniques revealed that an approximate bed height of 23 cm and a throat diameter of 5 cm led to an increase in gasification efficiency by approximately 17–18% for a downdraft gasifier. Incorporating AI in waste management practices and biogasification has the potential to increase efficiency, reduce waste generation, and improve biogas production quality, demonstrating the significance of AI in building sustainable waste management systems. The above studies provide evidence of the benefits of AI in waste management practices, biogasification, and gasifier design optimization, emphasizing the need for further exploration and development of AI techniques to attain sustainable waste management practices in the future.

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

No data, models, or code were generated or used for this paper.

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