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ORIGINAL RESEARCH ARTICLE

Machine learning for waste-to-energy processes: Resource evaluation, conversion efficiency, and environmental effects

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ABSTRACT

Waste-to-energy (WtE) technologies are increasingly important for sustainable waste management and circular economy practices, as they enable recovery of energy from municipal, agricultural, and industrial wastes while reducing landfill use and associated emissions. Despite this relevance, existing research on machine learning (ML) applications in WtE systems remains fragmented, with most studies addressing individual processes, specific algorithms, or isolated performance metrics, and lacking an integrated perspective across the full value chain. The objective of this work is to provide a comprehensive review of machine learning applications in WtE systems, covering resource evaluation, conversion efficiency, and environmental effects within a unified framework. The study is based on a systematic analysis of recent peer-reviewed literature reporting experimental validation or applied modeling in incineration, gasification, pyrolysis, and anaerobic digestion processes. The review indicates that machine learning models successfully capture the nonlinear and time-varying behavior of WtE systems, allowing accurate prediction of waste generation and composition, heating value, biogas yield, process efficiency, and pollutant emissions. Tree-based ensembles and neural networks show strong performance in feedstock assessment and conversion modeling, while data-driven soft sensors and surrogate models support real-time emission prediction and life-cycle impact evaluation. These findings demonstrate that machine learning offers practical benefits for improving operational stability, energy recovery, and environmental compliance in WtE plants, while also highlighting persistent challenges related to data quality, model transferability, and interpretability that should guide future research and deployment.

Keywords: Waste-to-energy, machine learning, resource assessment, incineration, gasification, pyrolysis, anaerobic digestion, biogas, emissions, life cycle assessment

1. Introduction

The increase of municipal solid wastes (MSWs), industrial residues, and agricultural by-products increases the burden on traditional waste management practices and releases greenhouse gases and local pollutants. The heterogeneous waste streams are converted with WtE technologies into heat, electricity, fuels and value-added products and finally more often considered as part of a circular economy. Thermochemical pathways—a selection of incineration, gasification and pyrolysis—and biochemical routes such as anaerobic digestion and co-digestion are based on coupling physical, chemical and biological processes. Their effectiveness is a function of feedstock, operating conditions reactor design and control settings. Traditional empirical correlations and mechanistic models frequently face difficulties in dealing with the strong non-linearity, time-dependent nature, as well as data noise of real WtE plants. Machine learning offers the possibility to model and control processes like this. Recent AI for waste management and WtE reviews report its applications in feedstock sorting, monitoring of process, energy output optimization, and emissions minimizing. With the improvement in sensing techniques and digitalization, ML algorithms have opened up new opportunities to extract reliable information through historical plant data, laboratory experiments, as well as online monitoring systems. More specifically, advanced ML algorithms such as neural networks, support vector machines, decision trees and random forests and gradient boosting are implemented to model, optimize and control high-temperature and low temperature treatment processes for organic waste [1]. The **Figure 1** shows how rising waste generation pressures traditional systems and drives the need for WtE technologies that convert diverse waste streams into heat, electricity, fuels, and useful products. It also highlights how machine learning supports these pathways through sorting, monitoring, optimization, and prediction.

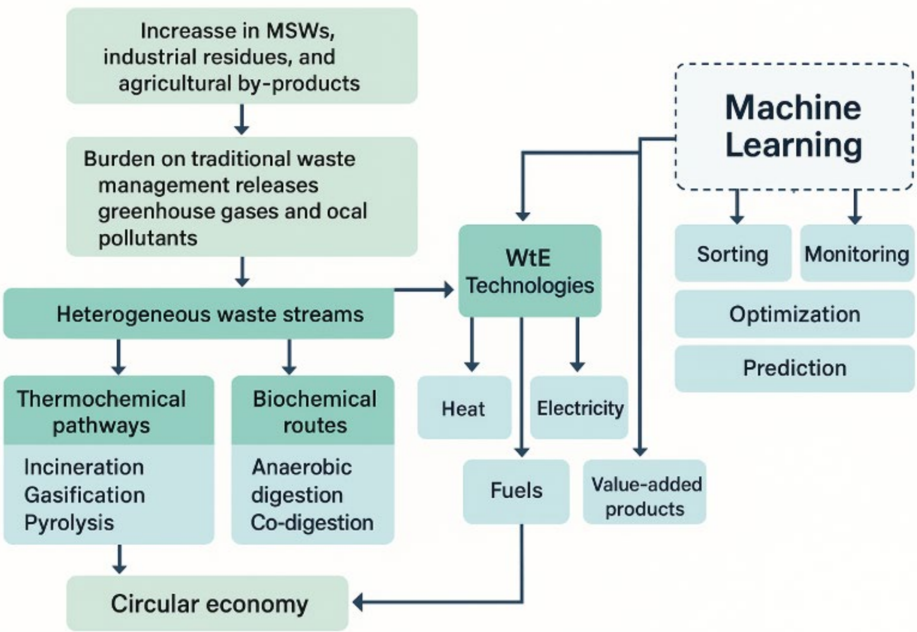

Figure 1. Role of Machine Learning Across Waste-to-Energy Pathways

In this review, the contribution of machine learning (ML) within the entire WtE chain is systematically summarized including waste characterization, process conversion efficiency as well as environmental impact and remaining challenges and potential issues that need to be addressed in future investigations [1,2,3]. It provides a synthesis of ML applications for waste since initial assessment and so addresses the fragmented nature of this literature. To overcome these limitations, the authors suggested using a ML-based model reduction that has the potential to cut down on computational cost, avoid frequent recalibration and facilitate its usage within online control systems [1]. ML can process time-series process data and detect subtle trends or deviations early on, which helps make timely operational changes and plant robustness [4]. In terms of chemicals and fuels generation, data driven analysis of large WtE datasets also may help in identifying better feedstocks, catalysts or alternative conversion routes [4]. The review also introduces ML in waste sorting process, calorific value prediction, biogas yield estimation and emission control, which provides a way for greater energy recovery and alleviated pollution [8–4]. Higher-end methods like deep learning, SVM and LSTM models contributed waste classification, generation forecasting and logistics, planning and predictive maintenance leading to minimizing downtime and extending equipment lifetime [11–13]. Decision support systems employing machine learning also enable the optimization of waste collection, circular economy goals and infrastructure planning by combining sensor and spatial data [10, 15, 16]. To sum up, the review shows that ML has potential scalable, adaptive, and dependable tools for efficient, stable and sustainable operation of modern WtE system at heterogeneous waste profile [12,14,24].

The studies included in this review were selected based on relevance to machine learning applications in waste-to-energy systems, with priority given to recent peer-reviewed journal articles reporting validated experimental or applied modeling results. Studies lacking clear methodology, performance metrics, or direct relevance to WtE processes were excluded to maintain consistency and analytical rigor.

Table 1. Machine Learning Applications Across the Waste-to-Energy (WtE) Spectrum

Waste Growth & Challenges	WtE Pathways	Machine Learning Role	Process Improvements	Typical Algorithms	Key Outcomes
Rising MSW, industrial residues, and agro-waste increase pressure on conventional systems.	Thermochemical routes (incineration, gasification, pyrolysis) and biochemical routes.	Handles non-linearity, time-varying data, and noise.	Improves sorting, monitoring, energy prediction, and emissions control.	ANN, SVM, decision trees, random forests, gradient boosting, LSTM, GANs.	Better energy recovery, improved stability, lower emissions.
Heterogeneous waste streams create operational constraints.	Converted into heat, power, fuels and products.	Provides fast, flexible, data-driven modelling.	Supports real-time adjustments in combustion and digestion.	Classical ML and deep learning models.	Greater resource use efficiency and reliability.
Field data and variable composition.	Physical, chemical and biological reactions.	Uses plant history, lab tests and online sensors.	Detects trends and anomalies early.	Multivariate input modelling.	Accurate prediction of heating value and biogas yield.
High uncertainty in feedstock quality.	Needs optimal reactor design and control.	Supports scalable and adaptable decisions.	Automated waste classification and logistics.	Predictive and interpretable models.	Reduced downtime and longer equipment life.
Traditional models fail under variability.	Efficiency depends on feedstock and settings.	ML must manage heterogeneity and noise.	Digital integration for real-time decisions.	Need interpretability and transparency.	Stable performance despite input variation.
Need modern sustainable waste approaches.	Supports circular resource use.	Bridges gaps between theory and practice.	Improves predictive tools for heat value and gas yield.	Deep learning for sorting and forecasting.	Higher efficiency through data-centric operation.

Waste Growth & Challenges	WtE Pathways	Machine Learning Role	Process Improvements	Typical Algorithms	Key Outcomes
Shift toward intelligent waste systems.	Hybrid routes and improved designs.	Uses advanced sensors and digital twins.	Adaptive control with ML insights.	Hybrid physical–ML models.	Smarter WtE plants with real-time intelligence.

Table 1. (*Continued*)

Table 1 illustrates that machine learning contributes across all stages of the WtE value chain, with its role shifting from prediction and classification at the resource assessment stage to optimization and control during conversion and emission monitoring. The comparison highlights that data-driven approaches are particularly effective in managing feedstock heterogeneity and operational variability, which remain key challenges in conventional WtE modeling.

2. Overview of Waste-to-Energy Technologies

Waste-to-energy (WtE) systems convert solid and organic wastes into useful energy forms such as heat, electricity, or fuel gases. These technologies fall into four major groups, each based on distinct thermal or biochemical pathways. **Figure 2** emphasizes the diversity of thermochemical and biochemical conversion routes available in WtE systems and underlines the varying levels of process complexity and control requirements associated with each pathway. This diversity explains the need for different machine learning strategies rather than a single unified modelling approach.

2.1. Mass-burn incineration

This refers to the direct incineration of MSW or refuse-derived fuel in a grate, fluidized bed or other type of boiler. The waste heat that is produced by the incineration of refuse serves to produce steam, which can be utilized for driving electricity generators or for district heating purposes. Today, modern flue-gas cleaning devices control the level of emissions of nitrogen oxides, sulfur oxides, and particles to a great extent and additionally enable the removal of dust och trace compounds like dioxins. As a result, modern plants use the high temperatures to make electricity follow clean – air standards and generate consistent energy. Nevertheless, incineration process remains the subject of issues including public acceptance gas emissions to atmosphere and toxic ash residues [4]. Therefore, recent advancements in the incineration field, including advanced incineration technologies along with more advanced machine learning strategies for online process optimization are important to reduce these environmental impacts and improve energy recovery efficiency [11,25]. However, even though it reduces waste volume by 85-90%, ashes are still ultimate residues that account for the remaining 10-15% of waste [26]. This ash, which is considerably smaller in volume, generally contains heavy metals and other pollutants and should be disposed safely [3].

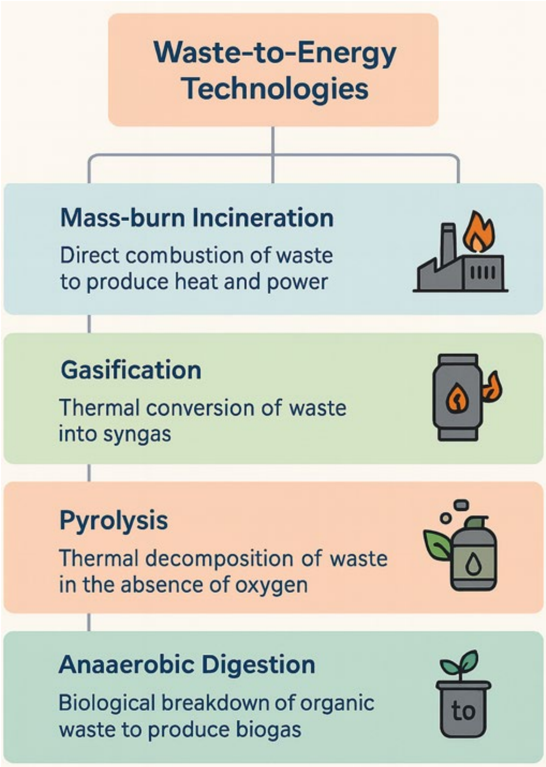

Figure 2. Overview of Waste-to-Energy Technologies

2.2. Gasification

It performs under low oxygen conditions and transforms the waste into a synthetic gas that contains high levels of carbon monoxide, hydrogen and methane. This syngas can be fed to internal combustion engines, to gas turbines, or further processed for chemical synthesis. Gasification provides more flexibility in controlling reaction conditions than direct incineration, and with a cleaner fuel product because some impurities remain in the char or are easier to capture during cleaning processes, depending on feedstock composition and reactor design. This thermochemical pathway of reaction, differing from incineration in being oxygen-deficient, represents an efficient conversion of organic solid waste to a syngas, a universal energy vector [25], [27]. This is done at high temperatures (generally in the range 500-1200 °C) and results in production of syngas as well as ash, biochar, having the characteristic percentage of yields affected by such factors as feedstock properties, gasifying agents or reactor working conditions. [1] Furthermore, the syngas, containing mainly carbon monoxide, hydrogen and methane can be directly burnt for power generation or forwarded to subsequence downstream process steps for value added fuels and process chemicals production thus offering a potential more flexible energy recovery and higher environmentally friendly option vs. direct incineration [25,28]. However, in spite of the possible advantages, pre-treatment and syngas purification processes are often necessary for gasification to remove contaminants from the gas stream also these may have significant cost implications—especially when applied to heterogeneous feedstock such as municipal solid waste [29].

2.3. Pyrolysis

It's based on the thermolysis of waste with no oxygen. The process produces a blend of solid char, condensate liquids and non-condensable gas portion. The process can be steered towards increased yield of gas, liquids or char by control over temperature, heating rate and residence time. This versatility lends to enabling a simultaneous energy recovery and material recycling particularly when char is obtained as the so-called carbon-rich product. Pyrolysis is a thermochemical process involving the breaking down of organic materials at high temperatures (300–800 °C) in an oxygen-free environment, and gives rise to bio-oil, biochar, and syngas with product distribution being a function of temperature, heating rate, as well as feedstock composition [30,31]. Unlike high-temperature, low-oxygen gasification process, pyrolysis is carried out at lower temperature and longer vapor residence time without the presence of oxygen, converting organic materials into liquid bio-oil with char and gaseous product as co-products [32]. This process has been used over the ages to produce charcoal from biomass and can convert municipal solid waste into fuel and benignly disposed materials such as char and metals [27]. Operation conditions during pyrolysis can be very well controlled for maximizing the solid char/lads, liquid bio-oil or gaseous products making it highly versatile waste-to-energy technology [27]. Advanced pyrolysis technologies (e.g., fast and flash pyrolysis) also optimize product recoveries by controlling heating rates and residence times to maximize the production of bio-oil that can be upgraded to transportation fuels or chemicals [5, 33]. The versatility of product production, varying from bio-oil to synthesis gas, makes pyrolysis a flexible process for waste valorization and in line with the principles of circular economy by reducing waste and maximizing the recovery of resources [26]. Nevertheless, one of the main shortcomings in pyrolysis is the requirement of feedstock quality control (commonly practiced does not include inert materials and moisture from municipal solid waste), which when available can decrease productivity and make operation more expensive [34–36]. In particular, fast pyrolysis (with rapid heating rate and a short vapor contact time around 500 °C) is designed for maximizing bio-oil production, contrasting with gasification that operates at higher temperatures focusing on syngas [37, 38].

2.4. Anaerobic digestion (AD) and co-digestion

It processes organic waste fractions such as food scraps, sewage sludge, farm manure, and agricultural crops. A consortium of microorganisms processes these substrates into a biogas rich in methane and a nutrient-loaded digestate. Biogas may be used to produce electricity or heat, and digestate can even be returned to the land to aid in nutrient cycling. Methane production yield increases Due to mixing of complementary substrates, process stability is increased and methane yield enhanced. This is a biological process under anaerobic conditions in which organic waste material is converted into biogas, a renewable source of energy, and digestate, a nutrient-rich soil amendment [26]. It is of interest for combustion to energy in biogas-fired power plants as well direct use, or upgrading into bio methane for direct vehicle fuel utilization and injection into natural gas grids [37]. Raw digestate, a by-product of anaerobic digestion has value as a bio-fertilizer and can reduce dependency on synthetic fertilizers, while simultaneously facilitating circular nutrient management [26]. Anaerobic digestion is a promising biotechnology for addressing the current energy crisis by using waste and nutrient recovery while not detrimentally affecting the ecosystem [39]. This process also lowers GHG emissions by avoiding methane release from landfills and fossil fuel substitution [5, 40, 41]. In addition to the challenges faced by anaerobic digestion, such as waste sorting and pre-treatment, as well as management of digestate [42,43], it is established technology for sustainable organic waste management and one of the circular bioeconomy pathways. Notwithstanding these challenges, developments in the AD process and associated technologies like co-digestion or thermal-alkaline pre-treatment are constantly increasing solubilization yield and methane production, making it more economically feasible for a wider range of applications [44, 45].

Environmental and energy performance among the rail routes varies widely. Uncontrolled landfilling entails a much greater environmental burden than thermal WtE for studies with energy recovery compared to fossil-based generation, as it appears evident from Table. Plants that thermally convert biomass to energy, such as integrated gasification–pyrolysis plants, have on average lower emissions per unit of energy. AD has the added value of nutrient recovery and gas reducing methane emissions from degrading biodegradable resources.

Nature of feedstocks together with nonsystematic process cause uncertainties in design as well as control application. This has generated an interest in data-driven methods which analyses historical process data to understand the interrelations between feedstock properties, operating conditions, energy outputs and emissions. These models can facilitate performance prediction, process control and environmental evaluation on advanced WtE systems. The comparison in **Table 2** shows that each WtE technology involves distinct trade-offs between energy recovery potential, environmental performance, and operational sensitivity to feedstock quality. These differences directly influence the type of machine learning models required, particularly with respect to handling uncertainty, nonlinearity, and data sparsity.

Table 2. Overview of Major Waste-to-Energy (WtE) Technologies

WtE Technology	Operating Principle	Main Products	Key Advantages	Major Limitations / Challenges
Mass-burn Incineration	Direct combustion of MSW or RDF in excess air using grate, fluidized bed, or boiler systems.	Heat, steam, electricity; bottom ash and fly ash.	Mature; strong volume reduction; efficient flue-gas cleaning; reliable energy.	Public acceptance issues; stack emissions; toxic ash; energy efficiency depends on waste composition.
Gasification	High-temperature treatment (500–1200 °C) of waste under oxygen-deficient conditions to form syngas.	Syngas, char, ash.	Higher control over reactions; cleaner fuel; suitable for chemical synthesis; flexible and environmentally better option.	Requires pre-treatment; costly syngas cleaning; feedstock variability impacts performance.
Pyrolysis	Thermal decomposition in absence of oxygen (300–800 °C) producing solids, liquids, and gas.	Bio-oil, biochar, non-condensable gases.	Flexible product distribution; suitable for material recovery; compatible with circular economy.	Sensitive to feedstock quality; product upgrading needed; higher costs for mixed MSW.
Anaerobic Digestion (AD) & Co-digestion	Microbial breakdown of organic waste in anaerobic conditions forming biogas and digestate.	Biogas (CH_4-rich), nutrient-rich digestate.	Suited for organic waste; methane production; nutrient recycling; reduces landfill methane.	Requires waste sorting; digestate management challenges; process sensitive to inhibitors.

These examples of waste-to-energy processes demonstrate the nonlinearity, operation variation, and data intensity that characterizes modern WtE systems. Variations of feedstock, reaction conditions and control at incineration, gasification, pyrolysis and anaerobic digestion do not allow purely empirical or mechanistic models. These are the properties driving the need for machine learning based on learning complex input–output relationships from operational and sensor data that leads to the methodology discussed in next section.

3. Machine Learning Methods in WtE Applications

Machine learning is now widely used to analyses, predict, and control the behavior of waste-to-energy systems. The methods reported in the literature can be grouped into several broad categories. **Figure 3** clarifies how different categories of machine learning models align with specific WtE tasks, ranging from static prediction to dynamic process control. The figure highlights that advanced and hybrid models become increasingly important as process dynamics and data dimensionality increase.

Based on the technology features of waste to energy discussed in previous section, this section introduces machine learning approaches that have been applied for model building, prediction and optimization of WtE systems. The choice of end-point ML methods is related to the process characteristics in terms of nonlinearity, temporal dynamics, data sample size and interpretability need. Hence each of the three applications services a different set of algorithmic families in feedstock assessment, performance analysis and environmental monitoring.

3.1. Supervised regression algorithms

Models including multiple linear regression, support vector regression, k-nearest neighbors, decision trees and random forest as well those based on gradient-boosting such as XGBoost and LightGBM and Gaussian process regression are commonly used to predict outputs like biogas yield, syngas composition, lower heating value or emission characteristics. These approaches model the relationship between composition, processing conditions and energetic or ecological counterparts. Neural networks, specifically ANNs, are also commonly used as they are capable of modeling complex non-linear relationships in bioprocess data and predicting outcomes such as biogas yield based on substrate composition, temperature, and pH [46]. Apart from these, other ML technologies like support vector machine, decision tree and random forest, Gaussian process regression etc., are also being used for modeling of organic waste management systems at the same time to implement resource recovery options [1]. Indeed, state-of-the-art machine learning methods such as deep learning and related hybrid models are becoming increasingly useful approaches in predicting energy production, optimizing operating conditions, and evaluation the environmental performance of diverse WtE processes [47, 48]. These models are indispensable to deal with the complexity and non-linearity of WtE systems, particularly where they comprise numerous input and output variables, in combination with different operational points [49].

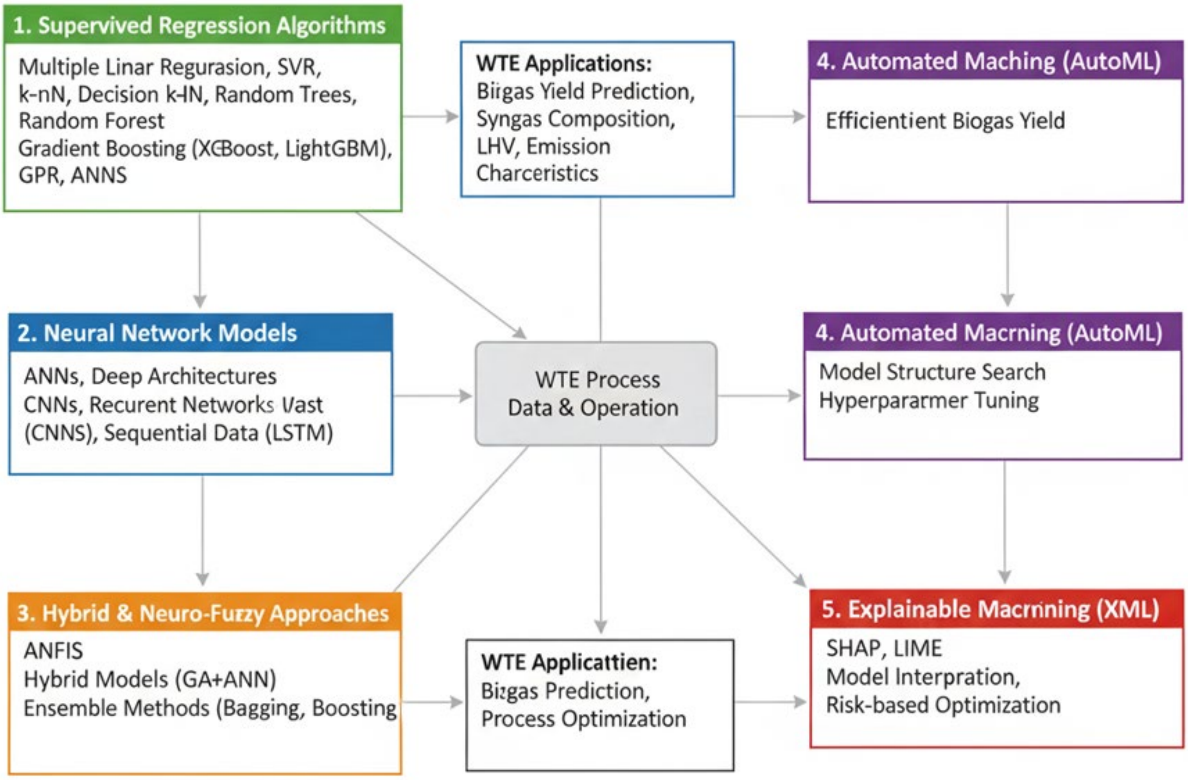

Figure 3. Classification and Application of Machine Learning Methods in Waste-to-Energy (WtE) Systems

3.2. Neural network models

They provide another major direction. Deeper architectures and feedforward networks have been applied to model nonlinear phenomena in combustion, gasification or digestion systems. For the image-based tasks, convolutional neural networks are widely used and among these use cases we have automated waste recognition and sorting. Recurrent models including LSTM networks model sequential process data and support the prediction of variables such as temperature profiles, gas flow rate or the stability of a digester. Aside from these basic methods, hybrid models which exploit the strengths of different ML algorithms (machine learning), such as genetic algorithm and ANN, have great potential for solving complicated optimization problems in WtE systems [50]. Ensemble methodologies, such as bagging that employ amalgamation of many models to result in a more stable prediction, are also becoming popular for improving predictive quality and minimizing the variance of prediction derived from WtE modeling [51]. The choice of a ML algorithm is an important factor for achieving the best results as different models have different prediction performance, generalization ability, stability and computational requirements [1,49]. For example, although Artificial Neural Networks are known for its capability to model complex non-linear relationships, they may lack interpretability while Support Vector Machines can perform excellent generalization even when limited number of data is available but might be difficult to apply on very large datasets [1, 52]. Gaussian Process Regression, a computationally expensive approach for big data sets compared to ANNs and SVMs, provides a stable non-parametric way which is very suitable for noisy and complex WtE data where it outputs uncertainty values of its estimates which are essential in risk-based process optimization [49].

Advanced ML methods such as deep networks, ensembles or hybrids with physics-informed models present high prediction accuracy on WtE but with substantial variability in the computation effort. Deep learning and hybrid models typically require more data, longer training time, and higher computational resources, that is not feasible in real-time applications for resource-poor plants. Tree-based ensembles and less complex regression models can therefore offer a good trade-off between the computational cost and effectiveness, making them more suitable for online monitoring and control. Accordingly, scale is still an important issue and model choices should be well-adapted to the available computational resources as well as operational constraints.

3.3. Hybrid and neuro-fuzzy approaches

They integrate knowledge-driven learning with expert-driven reasoning or optimization. ANFIS models are popular for biogas prediction due to their ability in dealing with imprecision of feedstock and process conditions. Genetic algorithms (GAs), particle swarm optimization (PSO), and other metaheuristic approaches are employed to optimize ANN and ANFIS parameters, or to develop hybrid models that can enhance prediction accuracy in gasification and AD research. Prediction is also enhanced by ensemble learning which combines multiple algorithms. Nevertheless, while recurrent neural networks can provide a lot of capabilities, such models can face potential difficulties like vanishing or exploding gradients during backpropagation – an issue usually mitigated by more sophisticated architectures such as Long Short-Term Memory networks that are well suited to capture long-range dependencies in sequential data [1, 49]. Ensemble methods which combine several high performing machine learning algorithms have been demonstrated to improve prediction performance in complex non-linear system such as biogas production [48]. Such enhanced robustness renders them especially suitable for predicting biogas potential and methane emissions as evidenced by the application of boosting algorithms with log-transformed data to cope well with highly skewed variables [53]. Although these state-of-the-art models provide great benefits, their “black-box” characteristic is an obstacle for understanding results as an important requirement in industry to make decisions jointly and transparently [46,54]. Reducing such interpretability gap has an active research field, and explainable AI techniques are widely used to provide model prediction explanations.

3.4. Automated machine learning (AutoML)

It has been proven to be an efficient tool for biogas yield prediction and waste composition modeling. Such frameworks automatically test multiple models’ structures, perform a hyper parameter search and return the best performing pipeline, which eases the job of researchers who have to work with complex datasets without much manual tuning. Not only does this automation speed up model development, it democratizes the use of advanced ML methods so that they become available to a wider group of WtE stakeholders and researchers. However, the successful employment of ML in WtE poses a range of challenges such as lack of high-quality and comprehensive data and further requirement for rigorous feature engineering to capture complex physicochemical interactions within these processes [50]. Moreover, it is very important to make the model interpretable and handle "black box" issue of most advanced ML algorithms, in order to gain trust and promote application of these techniques in industry WtE [4, 55]. Therefore, there is a growing interest in combining ML models with classic kinetic studies to obtain insights into overall reaction pathways and mechanisms [3]. Such integration is often performed using physics-informed machine learning, where physical laws are incorporated into architecture or loss function of models in order to improve predictive accuracy and scientific interpretability [56].

3.5. Explainable machine learning (XML)

These techniques (e.g., SHAP and LIME) are employed to interpret model outputs. Such tool identifies which feedstock property or operating factor has the highest influence on predictions, facilitates a clear process optimization and help in giving insights to operators on how models react. This interpretability is particularly important in digestion and gasification because of the nonlinear and inconsistent interactions between factors. Nevertheless, even when using these types of approaches to enhance transparency, the nature complexity of thermochemical phenomena such as gasification sometimes requires a further insight about relationships among governing mechanisms that SVR's/ANNs may hide [50]. To address this, there is an increasing interest in embedding fundamental thermodynamic and kinetic principles into the ML framework (physics-informed machine learning) to boost predictive accuracy of computational models as well as further our mechanistic understanding [1]. Overcoming these limitations of classical ML, the aforementioned hybrid models, such as PINNs [1] solve this "black-box" issue by incorporating physical laws within the architecture of neural networks to increase interpretability and generalization with sparse experimental data [58]. These methodologies could for example use thermodynamic equilibrium models, and ANNs being trained to indirectly estimate parameters that are notoriously difficult to measure, thus linking theoretical knowledge with empirical data [50]. **Table 3** indicates that model selection in WtE applications involves clear trade-offs between prediction accuracy, interpretability, and computational demand. While deep and ensemble models often deliver higher accuracy, explainable and hybrid approaches provide greater transparency, which is critical for operational acceptance.

Table 3. Machine Learning Methods in WtE Applications

ML Category	Typical Algorithms / Models	Main Applications in WtE	Strengths	Key Limitations
Supervised Regression	MLR, SVR, KNN, Decision Trees, RF, GBDT, XGBoost, LightGBM, GPR	Biogas yield, syngas quality, LHV, emissions prediction	Handles structured data; good for mapping inputs to outputs	Sensitive to data quality; limited for deep nonlinearities
Neural Networks	ANN, CNN, LSTM, Deep Networks, Ensembles	Nonlinear modelling, digester stability, waste sorting, thermal behaviour	Captures complex patterns; strong with images and sequences	Reduced interpretability; may need large datasets
Hybrid / Neuro-Fuzzy	ANFIS, ANN–GA, ANN–PSO, Ensemble Models	Biogas prediction, gasification optimization, methane estimation	Combines data-driven and rule-based learning; higher accuracy	High computational demand; possible black-box behaviour
AutoML	Automated model selection and tuning frameworks	Biogas yield modelling, waste composition forecasting	Fast development; reduces manual tuning	Needs high-quality features; interpretability concerns
Explainable ML (XML)	SHAP, LIME, physics-informed ML, PINNs	Identifying key drivers; improving control decisions	Improves transparency; links ML with physical laws	Complex thermochemical behaviour still hard to interpret

Pre-trained models are developed by utilizing the datasets collected from laboratory test, pilot test or full-scale WtE plants. They find applications both off-line, (for design studies, scenario analysis or performance benchmarking) and on-line (for soft sensing, real-time monitoring or advanced control).

3.6. Comparative Performance and Limitations of ML Models across WtE Processes

The applicability and performance of ML models in WtE applications strongly depend on the characteristics of the studied process, available data and technological targets. Tree-based ensemble learning techniques like Random Forest and gradient boosting exhibit generally great performance for predicting feedstock properties, heating values as well as emissions especially when the size of datasets is moderate and heterogeneous. Their capabilities for taking into account nonlinear interactions and indicating the importance of features make them suitable also for incineration and gasification units where interpretability is desirable for operational decision-making. Among the predictive models, ANN and DL models tend to have better performance for highly nonlinear systems such as in AD process and integrated WtE plant wherein the dynamics of processes are complex and time-dependent. Recurrent structures such as LSTM are well-suited to model dynamic behavior in biogas production and digester stability. However, these models need large and carefully-crafted datasets and may have low interpret-ability, which could limit their direct application in industrial control scenarios.

Hybrid or neuro-fuzzy systems are proposed as a trade-off between accuracy and interpretability by means of merging data-driven learning with rule-based reasoning or optimization. These strategies are particularly useful in anaerobic digestion and pyrolysis studies, where the lack of accurate knowledge on feedstock characteristics and operational conditions is substantial. They are mainly limited by high computational load and careful parameter design. Physics-informed and explainable machine learning models help overcome some of the shortcomings of purely empirical methods as physical constraints are encoded or interpretation of variable effect is provided. These models achieve better robustness under varying feedstock quality and lower risk of non-physical predictions, but at the cost of being non-trivial to develop given the necessary domain knowledge and computational resource requirements.

In general, no one machine learning model is globally superior to others on all the WtE processes. Process features, amount and quality of data, interpretability needs or context of deployment should guide model selection. Thus, a comparative application-specific analysis is necessary for a proper and robust implementation of the machine learning part in WtE.

4. Machine Learning for Resource Evaluation and Feedstock Assessment

Effective application of machine learning in waste-to-energy systems begins with accurate characterization of waste quantity and quality. This section focuses on ML-based approaches for resource evaluation, where data-driven models support early-stage decisions related to feedstock availability, composition, and energy potential. These predictions provide essential inputs for downstream conversion modeling and process optimization. **Figure 4** shows the major roles of machine learning in predicting waste quantity, assessing fuel properties, estimating biochemical potential, and supporting technology selection also summarizes how data-driven models help classify waste streams, estimate heating value, forecast biogas yield, and guide suitable WtE pathways.

4.1. Waste generation forecasting and composition estimation

Reliable prediction of waste amount and characteristics is essential for WtE system design, unit process sizing, and appropriate technologies to be implemented. The same machine learning techniques have been used to predict municipal solid waste (MSW) generation at city or regional level from socio-economic indicators, demographic factors and weather variables together with past records of waste generation. Assessment of waste composition and quality have been performed using image-based analysis systems and sensors to classify major waste fractions including plastics, metals, organics, and paper which are utilized in sorting processes as well as for preparation of refuse derived fuel (RDF).

Recent reviews on AI technologies applied to waste management suggest that, tree-based algorithms and artificial neural networks usually yield very high predictive accuracy, as declared values of R^2 are higher than 0.9 or more than 90% when reaching correct classification by sorting purpose. These models associate socio-economic characteristics (visual patterns) with waste type, contributing to the planning of resources and recovery of materials before energy conversion. This detailed characterization of waste streams is key in order to optimize pretreatment strategies, as directly affecting the efficiency and sustainability of following thermochemical or biochemical conversion pathways [3].

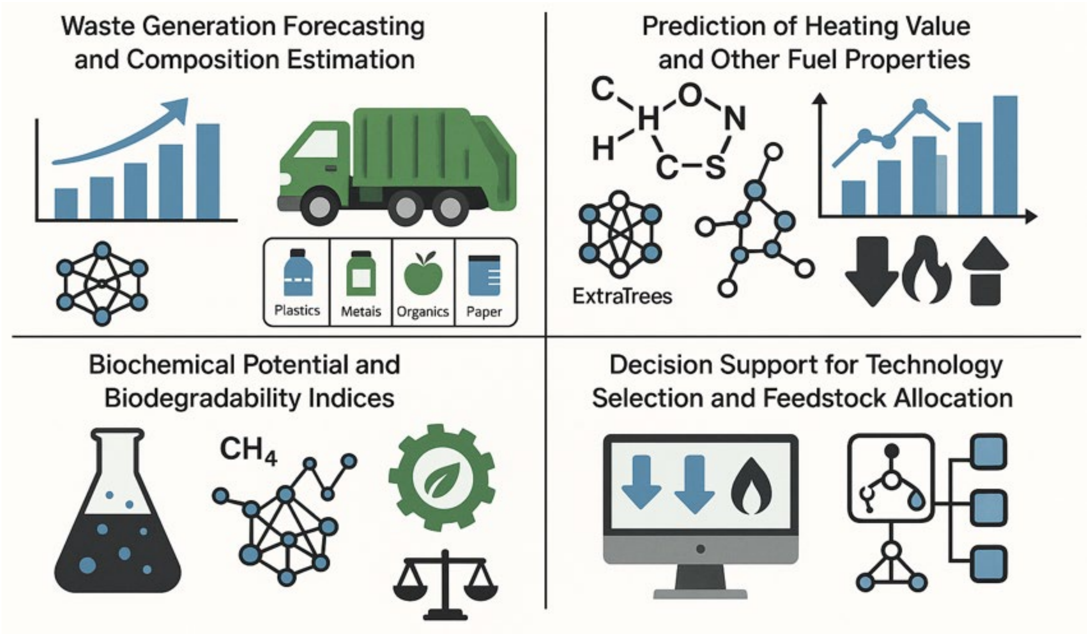

Figure 4. Machine Learning for Resource Evaluation and Feedstock Assessment

4.2. Prediction of heating value and other fuel properties

The net calorific value (NCV) of MSW is a key design parameter for incineration and gasification plants. The ensemble learning algorithms like Extra Trees, CatBoost, XGBoost and Random Forest have been utilized for the estimation of NCV using proximate as well as ultimate analysis data including carbon, hydrogen, oxygen, nitrogen, sulfur present in coal along with moisture and ash content.

For these model performances, test-set R^2 values of around 0.98 are reported for heating value predictions compared to classical regression correlations. The same technique is also employed to predict ash content, volatile matter and char yield for pyrolysis/gasification that can help in fast feedstock evaluation and optimized blending. In addition, ML models that consider feedstock particle size may improve the classification of a diverse set of plastic types including polyethylene and polypropylene by using input factors like ashless chemical components such as carbon, hydrogen, and oxygen [3]. This detailed characterization of feedstock properties is useful for modeling with better accuracy, the combustion or gasification behavior and also affects the design and operation of reactor system. These predictive abilities are essential to minimize process upsets, optimize energy production and lower emissions in WtE plants [1].

While several studies report high prediction accuracy, often expressed through elevated R^2 values, these results should be interpreted in light of dataset size and validation strategy. In many cases, strong performance is achieved using relatively small or laboratory-scale datasets, with validation limited to random train–test splits or cross-validation within a single data source. Such strategies may overestimate model generalization when applied to full-scale plants or different operating conditions. Explicit reporting of dataset size, temporal coverage, and validation approach (e.g., external validation, cross-plant testing, or time-series validation) is therefore essential to assess the robustness and practical applicability of the reported models.

4.3. Biochemical potential and biodegradability indices

The biochemical methane potential (BMP) and overall biodegradability of organic waste is typically estimated in the laboratory with anaerobic batch tests that are often time consuming. ML models that were developed based on feedstock characteristics (e.g., COD; volatile solids; C:N ratio; lignin content of biomass and nutrient content) are now implemented to predict BMP and the expected biogas quality.

ANN, RFR and SVN perform very well for the demand forecasting g model with hybrid models providing further enhancement according to Review Studies. AutoML-based algorithms have also been studied when ranking input variables in order to choose appropriate substrates and to design co-digestion scenarios based on their impact on biogas yield. Over and above yield, ML is fitted with potentiality to predict the kinetic parameters for anaerobic digestion ensuring effective control of retention times, organic loading rates to obtain maximum methane production and process stability [4]. This capacity of prediction also extends to the identification of potential inhibitory compounds or nutrient limitations, and provides preemptive modification of feedstock composition and bioprocess operation [59]. In addition, such models can compare the effect of biochar additions on anaerobic digestion systems and estimate increased CH_4 production and process stability by considering biochar characteristics and pyrolysis parameters [47]. This fine characterization enables development of customized biochar applications, optimizing the waste-to-energy route consideration for several organic substrates [47]. ML is also important in the development of the production and utilization of hydro char, a hydrothermal carbonization product which can be used to enhance the efficiency of anaerobic digestion as well as other WtE processes [60, 61]. These sophisticated machine learning approaches enable a more systematic and efficient usage of many different organic feedstocks, which in the end would drive faster transitioning from non-sustainable towards sustainable bioenergy recovery [47].

4.4. Decision support for technology selection and feedstock allocation

ML-enabled decision support systems, when coupled to multi-criteria decision analysis (MCDA) support the matching of waste streams with suitable conversion pathways: incineration, gasification and pyrolysis or anaerobic digestion. Such tools take into account energy generation, cost of operation and environmental constraints in allocating resources.

Such systems might suggest that high calorific, low moisture fractions should be redirected towards thermochemical routes and divert food waste or sludge to digestion. Through learning from data of the plants in operation, planners can use these models to test scenarios related to capacity enlargement, sharing feedstocks and globally optimizing WtE networks. We argue, however, that such smart systems should be also able to predict the best operating parameters for particular WtE technology on a basis of input nature and extend the conventional only-allocate approach towards a prescriptive energy recovery [4]. These frameworks even can incorporate the online operational data, to adapt the processing variables frequently in real-time for high efficiency and pollution-free operation [46]. Advances in this direction include the use of multi-objective optimization algorithms, sometimes hybridized with ML approaches, to simultaneously optimize economic competitiveness, environment impact and energy recovery for complex WtE systems [4]. These synergetic approaches benefit to a comprehensive system perspective, allowing data-based decisions reconciling various targets in sustainable waste management. Additionally, ML is applicable for the prediction of net biodiesel production through feedstock supply and provides accurate financial and environmental estimates for global uptake [62]. The knowledge gained from these models can support the increased efficiency, sustainability and environmental of biomass in the form of energy and be basis for a systematic adaptation towards strategic application targeting bioenergy and the conversation to biomass fuels technologies [63, 64].

5. Machine learning for conversion efficiency and process performance

Once feedstock characteristics are established, machine learning models are increasingly employed to improve conversion efficiency and operational stability of WtE technologies. This section examines how ML techniques are applied to predict process outputs, adjust operating conditions, and support real-time control across thermochemical and biochemical conversion routes. **Figure 5** demonstrates that machine learning enables coordinated optimization across multiple conversion pathways by linking operating conditions to performance indicators. This integrated view highlights the potential of ML to support real-time decision-making in complex WtE plants.

5.1. Incineration and grate-fired boilers

ML models are also commonly applied to predict combustion efficiency, boiler load and steam generation in municipal solid waste incineration plants. These models employ process parameters like waste feed material properties, grate speed, primary and secondary air flows and information of furnace temperature to calculate steam-production, boiler efficiency and major pollutants.

In the latest reviews on ML applied to WtE, ANN, Random Forest and gradient boosting models are mostly used for online prediction of combustion and process control. Data of case studies from AI supported incinerator adjustment indicate an improved operating stability, energy recovery and reduction of excess air.

Recent works include a combination of deep learning with combustion control to optimize the air distribution and waste feeding dynamically. These clouds exhibit more rapid dynamics and better power stability, and are at the heart of soft sensors and model predictive control (MPC) architectures in modern incineration facilities. These AI techniques can adjust operational parameters with high-resolution accuracy to keep the combustion in an optimal condition of efficiency and reduce emissions of pollutants and are more effective at recovering energy from a variety of waste streams [4,6]. In addition, it is possible to predict incinerators and grate-fired boilers equipment failures base on considering sensor data using ML algorithms which enables predictive maintenance to minimize downtime and prolong the lifetime of essential components [4].

5.2. Gasification and pyrolysis of waste and biomass

For MSW, plastics and biomass residues gasification/pyrolysis systems, ML application is used to predict syngas composition, H2 yield, tar generation, char properties of the product from fuel qualities and process conditions (temperature, residence time, equivalence ratio) and operational conditions (pressure or steam: fuel ratio).

In reviews related to biomass and waste conversion, ANN, SVR, and tree-based models are reported to have good predictability (usually $R^2 > 0.9$) of gas composition and process efficiency. Other works dedicated to plastic and PET gasification apply ML to optimize operational parameters aimed at enhanced hydrogen production or syngas quality.

For pyrolysis, ML has been used to establish the relationship between biomass composition and microwave pyrolysis parameters with biochar yield and quality. The models also predict liquid and gas fractions, which would aid in the selection of conditions preferable for energy conversion or materials reclamation. These predictive models are particularly important for maximizing the product yields and compositions of complicated thermochemical environments [3, 65]. Moreover, more sophisticated ensemble methods comprising various ML algorithms including decision trees, XGBoost, random forests, ANNs and SVMs were shown to achieve better predicting results for syngas yield, LHV or LHVs of other products of mixed municipal solid waste [50].

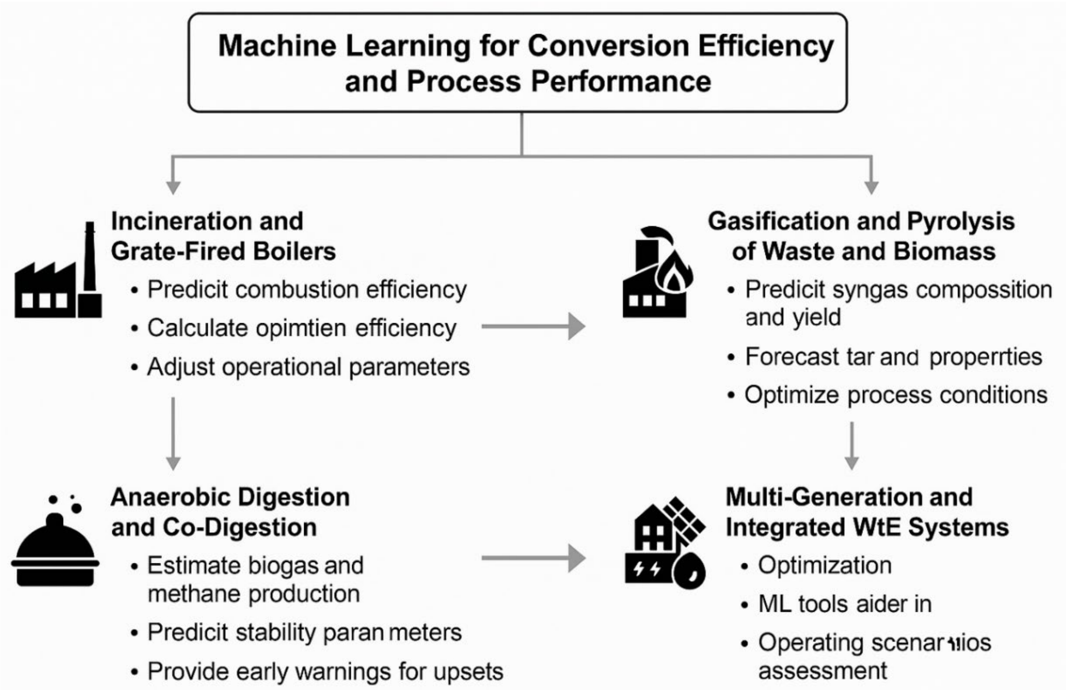

Figure 5. Machine Learning for Conversion Efficiency and Process Performance

5.3. Anaerobic digestion and co-digestion

The anaerobic digestion process is significantly influenced by the operation conditions, including temperature, pH, OLR and HRT, as well as the substrate properties [16]. ML models are used to:

- Estimate biogas production and methane yield from feedstocks and operating conditions.
- Predict stability parameters of VFA, alkalinity and VFA/alkalinity ratio.
- Divides digester states between a stable and unstable to provide early warnings for any upsets.

Recent reviews on AI in AD and co-digestion suggest that ANN, RF and ANFIS are commonly used, hybrid/ensemble methods help for better generalization when noise from sensor is present. AutoML-built tree models yielded accurate predictions of biogas production and ranked VS loading, temperature, and C:N ratio as the most important variables.

Explainable ML methods, such as SHAP analysis, are further applied to interpret the impact of feedstock composition, OLR and temperature on methane yield and process stability in order to make such models transparent for plant operators. Bayesian Networks and Extreme Gradient Boosting further improve the predictive performance by reasoning about uncertainty and taking a robust combination of weak models, respectively resulting in the translation (model) of qualitative observations to quantitative numbers for process selection and estimation of biogas yield [46]. Likewise, AI-enabled applications are being built for wastewater treatment processes in which machine learning models are used to forecast treatment and methane yield performances of anaerobic reactors, performing so much better than linear regression traditional models [66].

5.4. Multi-generation and integrated WtE systems

The ML methods also have been employed in multi-generation WtE systems by which taking MSW material into multiple energy products, e.g. electricity, heat, hydrogen and sometimes cooling or desalinated water.

Optimization of these integrated plants based on ML is demonstrated to lead to their exergy efficiency, load-following capability and also environmental performance enhancement. ML tools based on regression aid the operator in assessing a plethora of operating scenarios, and quickly adaptation of modes to varying feedstock quality or variations in energy price. These models such as the one in allow to make near to real-time decisions for efficient driving (resource allocation and energy production) of complex WtE systems [67-78]. Moreover, reinforcement learning approaches are being investigated to realize adaptive control techniques for WtE integrated plants, which can optimize operational parameters autonomously and achieve the best overall systems efficiency and economic performance in varying market conditions with feed stocks. It is apparent that the machine learning enables the energy conversion through waste become more efficient and produces cleaner outputs including optimizing operations, yield predictions and environmental contaminant reduction [79-88]. In addition to these established uses, there is growing research on ML approaches for the optimization of waste sorting and preprocessing, two essential operations impacting directly on the efficiency and environmental footprint of subsequent WtE conversion technologies [4]. Smart technologies including advanced sensors and data analytics as well as machine learning will significantly reshape the waste-to-energy industry with an ability to monitor and optimize processes in real-time for increased efficiency and flexibility [89-95].

6. Machine learning for environmental effects and emission control

Beyond energy recovery, environmental performance remains a critical dimension of waste-to-energy systems. This section addresses the application of machine learning for emission prediction, environmental monitoring, and life cycle impact assessment, completing the progression from resource evaluation to conversion performance and environmental compliance.

6.1. Soft sensing and prediction of air emissions

Waste-to-energy plants have to be operated within tight emission limits as regards NOx, SOx, CO, particulates, dioxins and furans, heavy metals and greenhouse gases. ML soft sensors employ regular plant measurements (e.g., furnace temperature, oxygen concentration, flowrates and waste feed properties) to predict emissions in real-time and to assist in automation control.

For incinerator NOx soft sensing, existing studies use gradient boosting, Random Forest and deep learning to predict NOx concentrations from operation data. These predictive models help optimize flue gas recirculation and selective catalytic reduction (SCR) following and provide NOx control stability during load changes. Artificial intelligence-based emission forecasting methods also cut down on control system action time and have averted short term spikes in emissions.

Machine learning models are also employed for predicting environmental impact and carbon intensity of process working conditions and syngas properties, helping in greener design and operation methodologies to gasification/pyrolysis systems. The predictive ability also includes the evaluation of environmental impact for biomass energy projects by analyzing environmental data and simulating ecosystem dynamics [96-105]. Furthermore, the precise estimation of waste generation and its emission potential using machine learning models provides a key source for prospective environmental planning in biomass to energy initiatives [106-115].

6.2. Support for life cycle assessment and scenario analysis

Among these, life cycle assessment (LCA) is and stays a central method for evaluating WtE options against landfilling, recycling and other waste disposal routes. Always those studies that are available come to the result that uncontrolled landfills load up environment more strongly than incineration or combined gasification–pyrolysis-based systems; in particular when energy recovery credits are considered.

There are two factors ML supports LCA with:

- Surrogate modeling of inventory outputs: Regression-based surrogate models estimate life cycle inventory indicators, such as GHG emissions and acidification potential, by process variables and feedstock attributes. There models provide a fast way to evaluate alternative scenarios.
- Integration with process models: ML based process simulators can be combined with LCA to explore large scale design spaces for multi generation WtE plants including energy outputs, conversion efficiencies and target emissions.

These methodologies allow policymakers to compare technology paths including the effect of energy, cost and environmental constraints under high uncertainty settings. Furthermore, complex and dynamic interactions between various environmental factors and WtE technology can be practiced using machine learning which helps to extend our horizon of sustainability [116-123]. In addition, for environmental impact assessment and optimization of resource allocation within WtE processes ML methods are able even to detect patterns and trends in emissions and energy use [124-125]. This potential enlarged by the capability of ML of handling vast amount of data (and therefore to consider those "latent links" between process conditions, waste quality and environmental performances that has previously been ignored) is aimed at being valued [126-128].

6.3. Monitoring of leachate, odour, and other environmental impacts

Environmental control of WtE is not only stack emission. A number of additional consequences have imposed the advent of ML applications to counteract them:

- Leachate quality prediction based on waste composition and landfill / thermal residues properties.
- ANN Oduor modelling developed from meteorological parameters and operating data of the plant to predict dispersion around WtE facilities.
- Leaching of heavy metals from bottom ash and fly ash for which classification models are used to determine safe reuse options in construction materials.

These models extend ML from predict emissions to assessing risks for the environment and recovering usable resources from process wastes. In addition, the incorporation of ML into LCA frameworks addresses major data limitations; conventional LCA requires large data collection efforts and can be demanding on computational resources [1,69]. Models developed based on machine learning can be alternative methods for complex LCA models and reduce the computational burden, with good prediction capabilities of environmentaly impact [129-131]. Table 4 outlines how different machine learning methods are applied to control and evaluate environmental effects in waste-to-energy systems. It groups the applications into emission prediction, environmental impact estimation, LCA support, pattern detection in plant data and monitoring of leachate, odour and ash-related risks. **Table 4** highlights that machine learning plays a central role not only in emission prediction but also in broader environmental assessment and compliance support. The summarized applications show that ML-based soft sensors and surrogate models can significantly enhance regulatory monitoring and sustainability evaluation in WtE systems.

Table 4. Machine Learning for Environmental Effects and Emission Control

ML Techniques Used	Purpose / Application	Key Inputs	Main Outcomes
Gradient Boosting, Random Forest, Deep Learning, ANN	Real-time prediction of NOx, SOx, CO, particulates, dioxins, heavy metals; emission forecasting	Furnace temperature, oxygen concentration, waste feed properties, air flowrates	Stable NOx control, optimized FGR & SCR, reduced emission spikes, faster response during load changes
Regression models, Hybrid ML, Deep Learning	Estimating carbon intensity, predicting syngas properties, ecosystem modelling	Operating data, syngas composition, biomass characteristics	Greener process design, improved carbon assessment, better planning for biomass-to-energy systems
Surrogate regression models, ML-coupled process simulators	Fast estimation of LCA indicators (GHG, acidification); scenario evaluation	Feedstock attributes, process parameters, conversion efficiency	Rapid evaluation of technology pathways; decision support under uncertainty; wide design-space exploration
ANN, Clustering, Ensemble Methods	Detecting trends in emissions and energy use; analysing dynamic environmental factors	Historical plant data, environmental datasets	Better sustainability insights, improved resource allocation, deeper understanding of latent links
ANN odour models, Classification models	Predicting leachate quality, odour dispersion, and heavy-metal leaching	Meteorological data, ash composition, waste properties	Risk assessment, safer reuse of residues, reduced local impacts; support for circular use of process wastes

7. Challenges and Research Gaps

Despite the rapid proliferation of ML applications in WtE systems, there exist barriers towards their further uptake and sustained usefulness.

7.1. Data quality and quantity

The reliability of the ML models for WtE is now a great challenge due to the lack of data. Many analyses on anaerobic digestion indicate that the training of biogas and methane yield models is carried out based on small laboratory-scale datasets, which leads to poor transfers for predictions made using full scale digesters under varying loading rates and compositions of feedstock. Models that predict train and validate well by cross-validation often become with lower accuracy, when they are used in long-term plant data generation, where the sensor noise, missing values, and operational disturbances tend to be larger. The same is true for the thermochemical WtE systems. In gasification and pyrolysis research, mass transfer models constructed based on controlled experimental data were reported to drop the prediction accuracy when used in industrial applications, as they cannot consider real operating variabilities sufficiently. Deficiencies of these sensor systems (e.g., in incineration plants) and patchy data logging mean that emission prediction models are less stable in time for NOx and CO, where short-term training leads to neglect of seasonal and operationally sensitive behavior. These examples demonstrate that inadequate data volume and quality can directly affect the robustness of a model, serving as a barrier to practical use.

7.2. Heterogeneity and non-stationarity

Furthermore, during the operation of WtE systems, feedstock heterogeneity and temporal variability also complicate the utilization of machine learning. The composition of MSW shows great differences by location, season and socio-economic factors, posing domain shifts that are difficult to handle for static models. Some studies have found that models calibrated for one plant or region tend to perform poorly at other sites displaying different waste characteristics. The model is also dependent on the stationarity in noise (and is thus sensitive to instrument aging, calibration work and process drift over time). In AD, changes in microbiome activity with volatile solids and/or temperature can lead to system dynamics that fall outside those covered during training. Moisture content and more generally the prescription of calorific value over time in incineration/gasification plants causes that process behavior becomes dynamic with respect to these parameters, which undermines the use of fixed-parameter models. Such observations highlight the relevance of adaptive, transfer or continual learning approaches to keep predictive performance under real operational environment.

7.3. Limited interpretability

Despite achieving high-predictive accuracy, ensemble models and deep neural networks are used as black-box systems. Recent investigations of explainable ML for both AD and gasification show that feature-importance methods as well as local explanation tools can be useful, but few guidelines exist for interpretation or to translate model insights into operational strategies.

7.4. Integration with Physical and Mechanistic-based Methods

The majority of published work is based on purely empirical model, i.e., without mass balance, energy balance, reaction kinetics and transport limitations. This constrains generalization, and predictions outside the regime in which a model was trained may fail to satisfy physical constraints. The physics-informed ML, grey-box modelling and hybridized applications between mechanistic equations and data-driven com ponents represent relative new fields in WtE research.

7.5. Deployment and cyber-physical constraints

Availability, fail-safe operation, latency and cyber-security need to be carefully considered when integrating ML models into real control systems of plants. Very limited numbers of studies bring you to the operational stage, while most case studies are still at offline, simulation or pilot-plant status. This gap reflects the requirement to research integration and validation of industrial-level ML.

7.6. Standardization and benchmarking

The sets of predictors, model forms, and validation procedures differ widely between studies. Such discrepancies restrict meaningful comparison of results and do not facilitate accumulation of knowledge. Benchmark data sets are scarce for AD, gasification and incineration due to commercial, regulatory and confidentiality issues in the sharing of open data.

8. Future Research Directions

It is indeed possible to further improve the position of ML in WtE systems through several promising research directions.

8.1. Physics-informed and hybrid models

Physics-informed and hybrid ML models provide a practical route for enhancing model accuracy and deployment in WtE systems by integrating process understanding within data-driven frameworks. A few recent works show how the addition of mass and energy balance constraints into NN architectures leads to enhanced prediction robustness in gasification and pyrolysis processes, especially under extrapolative operating conditions where entirely data-driven models often predict physically unrealistic results. For instance, hybrid gasification models based on equilibrium-based syngas composition equations and neural networks have reported better robustness in predicting hydrogen and carbon monoxide yield for various equivalence ratios and feedstock moisture content.

In anaerobic digestion, physics-based methodologies have been employed by integrate deration of forms such as first-order or ADM1-like models with machine learning models. In these realizations, the ML component is trained to predict hard-to-measure biological parameters, whereas system dynamics are based on mechanistic equations. Hybrid models, such as ANN combined with mathematical equations, have achieved better long-term prediction of methane yield and stability monitoring compared to single neural networks under organic loading shocks or temperature variation. Applications in practice have also been reported on emission monitoring of incineration plants, where soft sensors combine combustion stoichiometry and flue-gas relations by means of regression or ensemble models. These hybrid soft sensors retain its predictive ability when the excessive air ratio or the garbage composition changes and can be applied to control NOx during actual incineration for emission regulation.

Nevertheless, some barriers still exist to the successful application. Hybrid and physics-informed models need more extensive collaboration between domain experts and data scientists, careful model calibration and higher computational cost. Nevertheless, the models have been documented in reported cases to achieve a good trade-off between accuracy, interpretability and physical consistency which are highly desirable for industrial scale deployment where trust and operational stability is paramount.

8.2. Explainable ML and operator-centric tools

Future work should stress interpretability, such as feature- importance analysis and visual analytics that are supportive for operational decision-making. Tools like SHAP values, partial dependence plots, and rule-based surrogates make it possible to translate the ML results into operational congruent advice regarding the control of such plants and hence make them more acceptable for plant operators and control engineers.

8.3. WtE digital twins

Some of its successful applications in industry are the combination of real-time data streams, ML models and process simulators in digital twins that provide a way towards monitoring at all times (and detecting early issues), predictive maintenance, and scenario testing. Research on digital twins in power generation and process industries can be generalized to WtE systems, but with a focus on waste heterogeneity, ash behavior and emission goals.

8.4. Federated and transfer learning

The lack of cross-company and regional sharing restricts the generation of generalized WtE models. Federated learning and transfer learning are techniques that enable the utilization of the knowledge from several plants avoiding to pool raw data. Such methods may mitigate overfitting, increase model robustness and better leverage sparse datasets.

8.5. Multi-objective optimization under uncertainty

WtE systems have to be designed and run taking account the trade-off between energy, cost, emissions-controlled technologies and resources recovery in face of uncertain waste composition and market conditions. Using ML in conjunction with EO and UA can help decision makers to grasp trade-offs and robust solutions under changing conditions.

8.6. Linking ML with policy and social approval

WtE initiatives may be evaluated in a transparent manner, on the basis of GHG balance indicators, health metrics and circular economy credits (via ML quantification) of emissions assessments. Such instruments could serve to assess environmental performance for regulators and local stakeholder, and in combination with transparent communication or sustainable operation practices they might even foster acceptance.

9. Conclusion

This review has presented a comprehensive and integrated assessment of machine learning applications across the entire waste-to-energy (WtE) value chain, spanning resource evaluation, conversion efficiency, and environmental impact assessment. By synthesizing studies from thermochemical and biochemical pathways, the analysis demonstrates that machine learning offers a practical means to address the inherent nonlinearity, variability, and data intensity of modern WtE systems. Data-driven models have shown strong capability in predicting waste characteristics, energy yield, process stability, and emissions, while also supporting real-time monitoring, optimization, and decision-making. Compared with traditional empirical and mechanistic approaches, machine learning provides faster prediction, adaptive learning, and improved handling of heterogeneous feedstocks and dynamic operating conditions. At the same time, the review highlights that high predictive accuracy alone is not sufficient for reliable industrial adoption. Persistent challenges related to data quality, limited transferability across plants, lack of standard benchmarking, and reduced interpretability of complex models continue to constrain large-scale deployment. The discussion indicates that hybrid and physics-informed machine learning, explainable models, and digital twin frameworks represent promising directions to balance accuracy with physical consistency and operational trust. Overall, this work clarifies the current state of knowledge, identifies key gaps, and outlines research priorities that can guide both future academic studies and practical implementation of machine learning in sustainable waste-to-energy systems.

Abbreviations

Abbreviation	Full Form
AD	Anaerobic Digestion
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANFIS	Adaptive Neuro-Fuzzy Inference System
AutoML	Automated Machine Learning
BMP	Biochemical Methane Potential
CNN	Convolutional Neural Network
CO	Carbon Monoxide
CO_2	Carbon Dioxide
DL	Deep Learning
DNN	Deep Neural Network
GBDT	Gradient Boosting Decision Tree
GHG	Greenhouse Gas
GPR	Gaussian Process Regression
HRT	Hydraulic Retention Time
LCA	Life Cycle Assessment
LHV	Lower Heating Value
LIME	Local Interpretable Model-Agnostic Explanations
LSTM	Long Short-Term Memory
MCDA	Multi-Criteria Decision Analysis
ML	Machine Learning
MSW	Municipal Solid Waste
MPC	Model Predictive Control

NCV	Net Calorific Value
NOx	Nitrogen Oxides
OLR	Organic Loading Rate
PINNs	Physics-Informed Neural Networks
PSO	Particle Swarm Optimization
RDF	Refuse-Derived Fuel
RF	Random Forest
RNN	Recurrent Neural Network
SCR	Selective Catalytic Reduction
SHAP	SHapley Additive exPlanations
SOx	Sulfur Oxides
SVM	Support Vector Machine
SVR	Support Vector Regression
VFA	Volatile Fatty Acids
WtE	Waste-to-Energy
XML	Explainable Machine Learning

Author Contributions

Swapnil S. Chaudhari contributed to the conceptualization of the review, literature collection, and drafting of sections related to machine learning foundations and data-driven modeling in waste-to-energy systems. **Kundan Kale** provided inputs on waste management practices and system-level interpretation from a civil and environmental engineering perspective. **Manisha Raghuvanshi** contributed to the analysis of environmental impacts, sustainability indicators, and life cycle assessment aspects. **Torana Kamble** supported the review and synthesis of machine learning algorithms and intelligent decision-support approaches. **Ramsing Thakur** contributed domain expertise on thermochemical waste-to-energy technologies, including incineration, gasification, and pyrolysis, and reviewed technical accuracy. **Sagar Arjun Dalvi** assisted in reviewing literature related to anaerobic digestion, biogas production, and biochemical conversion processes. **Prashant Ashok Patil** contributed to comparative analysis of machine learning methods and preparation of summary tables and figures. **Shital Yashwant Waware** supported manuscript editing, reference organization and consistency checks across sections. **Anant Sidhappa Kurhade** conceived and supervised the overall study, defined the scope and structure of the review, integrated contributions from all authors, performed critical revisions, finalized the manuscript, and served as the corresponding author, ensuring scientific coherence and quality.

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Conflict of interest

The authors declare no conflict of interest

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