

Machine Learning for Analyzing the Biowaste to Wealth Approach: A briefreview.

Chandolu Nagamani^{1*}, Yeti Dhana Rao², M.V.S Pavan Kumar³, K. Rajendra⁴, Samuel John Gosu⁵, P. Dhyva Stuthi⁶, B. Kiran Babu⁷ and K. Poornima⁸

^{1,*}Dept. of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A. P., India.

²Dept. of Physics, Rajeev Gandhi Memorial College of Engineering and Technology, Nandyal, A. P., India.

³Dept. of Mechanical Engineering, Sasi Institute of Technology and Engineering, Tadepalligudem, A. P., India

⁴Dept. of Mechanical Engineering, Aditya University, Surampalem, A. P., India.

⁵Dept. of Basic Sciences and Humanities, Narasaraopet Engineering College, A. P., India.

⁶Dept. of Basic Sciences and Humanities, Usha Rama College of Engineering & Technology, A. P., India.

⁷Dept. of Botany and Microbiology, Acharya Nagarjuna University, Guntur, A. P., India.

⁸Dept. of Physics, Aditya University, Surampalem, A. P., India.

***Corresponding Author:**

Chandolu Nagamani

ABSTRACT

The biowaste to wealth is a pillar of circular bioeconomy tactics, which aim at turning organic waste like food wastage, farm residues and city sludge into a range of high value products such as biogas, biofertilizers, biochar and platform chemicals. Models based on conventional methods which depend on mechanistic kinetic equations such as Monod or Gompertz, frequently have problems with the intrinsic heterogeneity of feedstocks nonlinear microbial dynamics and multiple process variables. Machine learning (ML) stands out as a revolutionary tool that can be used to overcome these problems. It utilizes data driven algorithms to forecast output, tweak inputs and allow live control with an accuracy never seen before. In this work discusses in detail the use of machine learning in the main recycling pathways such as anaerobic digestion (AD) for the production of methane, thermochemical methods such as pyrolysis and gasification for the production of syngas/bio-oil composting for the production of nutrients, rich humus and fermentation for the production of biohydrogen.

Keywords: Machine learning; Biowaste; Bioeconomy; XGBoost; SVM.

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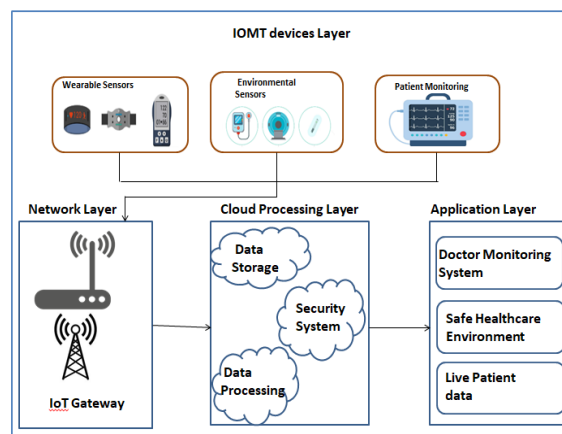
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INTRODUCTION

The biowaste to wealth concept symbolizes a significant shift in sustainable waste management, whereby large quantities of organic residues including food scraps, agricultural husks, crop residues and municipal sludge are converted into economically valuable products such as biogas, biofertilizers, biochar and platform chemicals[1]. Worldwide the amount of biowaste generated is more than 2 billion tons per year, which is nearly 30% of the total municipal solid waste and moreover, disposal through landfills and incineration contributes over 8% of anthropogenic greenhouse gas emissions. Such wastefulness not only exhausts limited resources but worsens climate change through methane emission[2].

Biowaste valorization techniques like anaerobic digestion (AD) to produce methane, rich biogas, thermochemical pyrolysis/gasification for syngas and bio-oils aerobic composting for nutrient, rich humus, and microbial fermentation for biohydrogen, harmonize with circular bioeconomy strategies aiming at closing material loops[3], [4]. Yet these methods still suffer from problems caused by



the variable nature of feedstock, the diversity of microbial communities, and the nonlinearity of processes, which makes the conventional empirical methods insufficient for widespread application[5].

Traditional modeling in biowaste valorization mostly depends upon mechanistic frameworks such as the

Gompertz equation for modeling the kinetics of biogas, Monod kinetics for microbial growth or using ADM1 for multi-step AD hydrolysis/acidogenesis/methanogenesis [6]. These models require accurate parameter estimation, fail to account for the synergies in co-digestion and do not work well with real life situations like temperature fluctuations (5C) or inhibitor accumulation (VFA > 5000 mg/L)[7], [8], [9]. CFD modeling for reactor design requires a lot of computational resources, whereas RSM restricts multivariate exploration. As a result, the lab to pilot scale up has <70% predictive fidelity thus limiting commercialization[10].

Machine learning (ML) provides a solution to these problems through the use of large, heterogeneous datasets to discover hidden patterns predict outcomes and optimize controls with outstanding accuracy (R consistently >0.90, 0.99). Supervised algorithms neural networks (NNs, LSTMs, CNNs), tree ensembles (Random Forests, XGBoost), and support vector regressions are very good at learning complex nonlinear relationships[11].

As an example XGBoost applied on pyrolysis datasets pinpoints lignin content and temperature (700°C) as the most important variables determining biochar higher heating value. Unsupervised clustering categorizes waste materials for the best blending, while reinforcement learning (RL) is used for the automatic dynamic adjustment of organic loading rates in anaerobic digestion (AD) pilot plants[12]. Hybrid physics informed NNs incorporate conservation laws thus extending the model's validity across scales. A meta, analysis of the literature demonstrates that ML can be expected to lower prediction RMSE by 40 to 60% when compared to kinetics models[13], [14].

2. Fundamentals of ML in Waste Processing

ML algorithms take in inputs such as volatile solids (VS), C/N ratio, temperature and pH to predict outputs like methane yield or biochar properties. Supervised learning is a good fit when predicting the yield; unsupervised learning can be used for clustering types of wastes, reinforcement learning is suitable for process control[15]. One of the main neural network (NN) methods is the Multilayer Perceptrons (MLPs), LSTMs for time series AD data, CNNs for the spectral analysis of waste compositions. Examples of tree based models are Random Forests (RF) and XGBoost which can be used to determine the importance of features. Support Vector Machines (SVM) are particularly beneficial when dealing with high dimensional data such as pyrolysis kinetics[16]. **Table 1** describes various types of models and algorithms for data analysis.

Gaussian Process Regression (GPR) is a technique that is capable of offering uncertainty quantification when dealing with small datasets. Hybrid models integrate ML with a physical understanding for enhanced interpretability. Data preprocessing such as normalization/feature selection through PCA/SHAP helps to resolve the issue of data imbalances that are typical in biowaste[17], [18]. **Fig. 1** describes different models of ML.

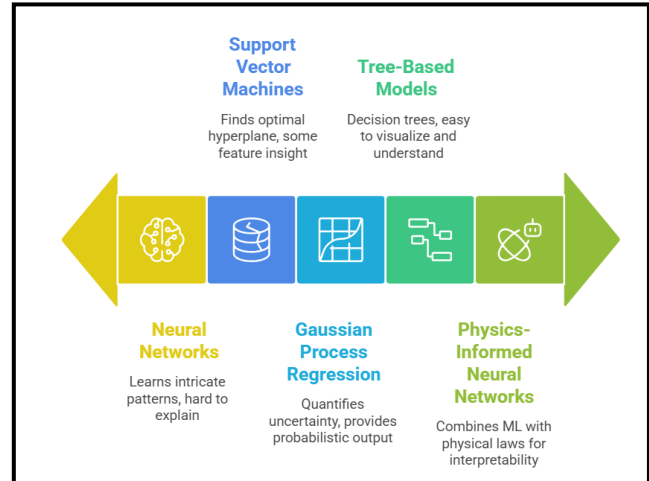


Fig. 1 Different types of models for ML

Table 1 Various types of models and algorithms for data analysis

ML Category	Algorithms	Data Requirements	Biowaste Fit
Supervised Regression	NN, XGBoost, SVM	Labeled yields (1000+ samples ideal)	Yield/emission prediction
Ensembles	RF, LightGBM	Noisy, imbalanced data	Optimization under variability
Probabilistic	GPR, Bayesian NN	Small datasets	Uncertainty in feedstocks
Deep Learning	LSTM, Transformers	Time-series (>5000 points)	Real-time monitoring

2.1 Anaerobic Digestion: ML-Driven Optimization

AD hydrolyzes, acidifies, acetates and methanates biowaste into CH₄/CO₂. ML models predict the yields from co digestion mixtures for example food waste + manure. An AutoML tree based tool on few year industrial data has detected fats/oils/greases (FOG) and poultry waste as great yield enhancers with RF reaching RMSE=0.075 m/kgVS[19]. XGBoost has beaten the baselines (R=0.895) giving daily input more importance than VS efficiency. Deep NNs after microwave pretreatment have scored R=0.9946 using VS/TS and SCOD/TCOD ratios as inputs. LSTM models predict the buildup of VFA thus help in avoiding instability. SHAP analysis indicates temperature and OLR as the main factors[20], [21].

2.2 Thermochemical Pathways: Pyrolysis and Gasification

Pyrolysis produces biochar/bio-oil gasification (air/steam) yields syngas. ML is capable of managing combinatorial inputs: biomass composition, temperature, catalyst. XGBoost on various datasets forecasted biochar

yield/HHV, with microwave power as the leading feature. RF/GBM for microwave, assisted pyrolysis (MAP). ANN kinetic models derived from lignin/hemicellulose ratios had deviations of <15%[22].Table 2 describes various ML models for analysis different processes[23], [24].

Table 2Analysing ML models in various processes

Process	ML Model	Key Inputs	Outputs Predicted	Accuracy
Pyrolysis	XGBoost	Temp, power, lignin %	Biochar yield, HHV	R ² =0.92
Gasification	SVM/RF	ER, steam ratio	Syngas composition	R ² =0.90
HTL	GBM/GPR	Pressure, residence time	Bio-crude yield	R ² >0.90

2.3 Challenges in ML Deployment

Machine learning (ML) applications for biowaste valorization face significant challenges due to the scarcity and poor quality of data which are further complicated by regional biases forexample EU focused datasets on livestock manure, whereas India has a variety of agro, waste such as rice husks and sugarcane bagasse. Synthetic data generation using Generative Adversarial Networks (GANs) can be a good option to solve this problem, as it allows the model to be trained on more data, thus improving the model’s robustness[25]. ML ensembles, L1/L2 regularization, and stringent k, fold cross, validation are some of the methods that are used to prevent the problem of overfitting, which is frequently seen in deep neural networks trained on noisy bioprocess data and refers to the model that learns the training data too well but fails on the test data. Scalability is still a very important factor for the commercialization of products and thus lightweight edge ML frameworks like TinyML are required for real, time monitoring in on site anaerobic digesters as well as composting units to be deployed at the industrial scale[26], [27].

Regulatory bodies are less willing to trust black box models as they cannot understand the decision making process but such regulatory and market constraints can also be removed by leveraging eXplainable AI (XAI) techniques that use the local explanation for every prediction and globally measure feature importance to uncover which input variables have a more significant effect on the model outputs through SHAP and LIME[28]. **Table 3** briefs Various types of models and processes for data analysis. Besides that, the ML integration with Life Cycle Assessment (LCA) and Techno Economic Analysis (TEA) must be achieved for the comprehensive consideration of sustainability, thus giving the environmental aspects a balanced weight with the financial ones for the largescale biowaste to wealth conversion[29].**Fig. 2** explains ML models in agro waste management

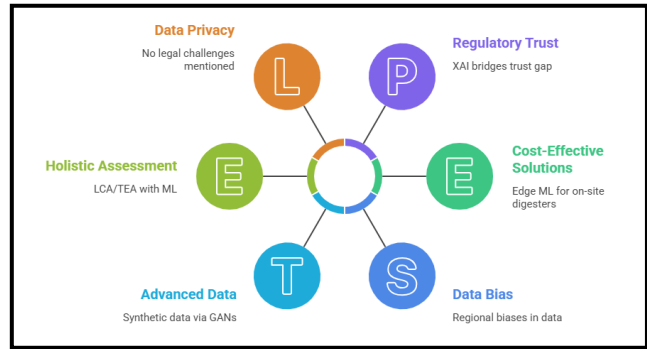


Fig. 2ML models in agro waste management

Table 3 Various types of models and processes for data analysis

Process	Model	Dataset Size	R ² /RMSE
AD Co-digestion	Tree-AutoML	8y industrial	RMSE=0.075
Microwave AD	Cascade NN	Literature	0.9946
Pyrolysis	XGBoost	200+	>0.9
Composting	RF/ANN	Lab-scale	0.88

3. Biowaste Characteristics and Conversion Technologies

Biowaste features depend largely on the kind of feedstock and thus each one differently impacts the efficiency of biowaste conversion in the biowaste to wealth scheme. Among others, agro, industrial wastes like rice husks, sugarcane bagasse and palm oil residues which are dominating in India are mainly made up of lignocellulose and poorly balanced nutritionally, whereas municipal organic waste has a high moisture content and a diverse microbial consortium[30]. These raw materials vary in their proximate composition volatile solids (VS) ash content and biodegradability and therefore to improve accessibility they need to be preprocessed by methods such as shredding or hydrothermal treatment[31].

Four primary technologies are commonly used in the conversion of organic material to energy or fertilizers anaerobic digestion (AD) to produce biogas, composting to create biofertilizers, pyrolysis to generate bio-oil and microbial fuel cells (MFC) to produce bioelectricity. The success of these conversion processes largely depends on the extent of various parameters[32]. Among them are the optimal carbon to nitrogen (C/N) ratio, pH (6.5, 7.5), temperature and the presence of inhibitors such as lignocellulose tannins or heavy metals which hinder hydrolysis. Traditional modeling which depends on black box kinetics is less capable of handling nonlinear dynamics and sitespecific variabilityhence the justification for data driven machine learning (ML) solutions[12].

4. Datasets, Preprocessing, and Feature Engineering

Most of the time, datasets for biowaste to wealth ML research come from publicly available repositories. For example, Waste Classification dataset from Kaggle has labeled images for sorting and Bio, AD sets have anaerobic

digestion parameters. Besides being extremely helpful, these datasets have a few limitations like scale and regional bias[33]. Additionally, some specialized data such as composting kinetics time series from UCI Machine Learning Repository, however these features (pH, temperature or C/N ratios) are not standardized, which makes it difficult to transfer the models directly[34].

Preprocessing intends to fill in these gaps mainly through the class balancing augmentation techniques such as SMOTE (Synthetic Minority Over sampling Technique) in the prediction of waste types combined with normalization and outlier removal employing the IQR method[35]. Feature engineering is a vehicle for better performance dimensionality reduction via PCA provides a more manageable set of high dimensional spectral data features whereas domain specific features provide the inputs with more depth. By quantifying the contribution of each feature in the prediction, SHAP (SHapley Additive exPlanations) keeps the model transparent and shows the main factors, such as lignocellulose content over less influential metadata[10]. **Fig. 3** shows diagrammatic representation of data preparation process

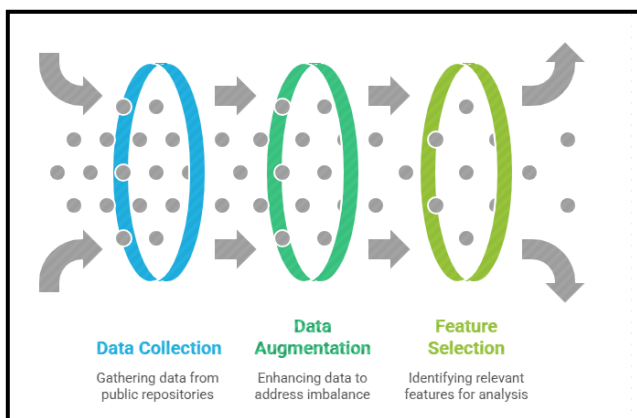


Fig. 3 Diagrammatic representation of data preparation process

Conclusion

The biowaste to wealth paradigm is a radical innovation that can reshape the circular bioeconomy, where machine learning (ML) plays a crucial role in the transformation of organic waste streams such as agricultural residues, municipal solid waste and food scraps into value added products including biofuels, biofertilizers and biochemicals. Historically, the biowaste management sector has struggled with inefficiencies in processes such as anaerobic digestion (AD), composting and pyrolysis, where empirical models have often been unable to accurately estimate yields because of complex, nonlinear interactions among parameters like the C/N ratio, pH, temperature and lignocellulose. Machine learning mitigates these problems by adopting data, centric methods ranging from supervised algorithms such as Random Forests and Support Vector Machines for waste classification and yield prediction, and deep learning techniques. However, there is also huge potential in the integration of AI, IoT at the edge. ML

powered biowaste valorization not only reduces environmental pollution but also releases economic capacity thus paving the way for sustainable resource efficiency in the era of bioeconomy

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