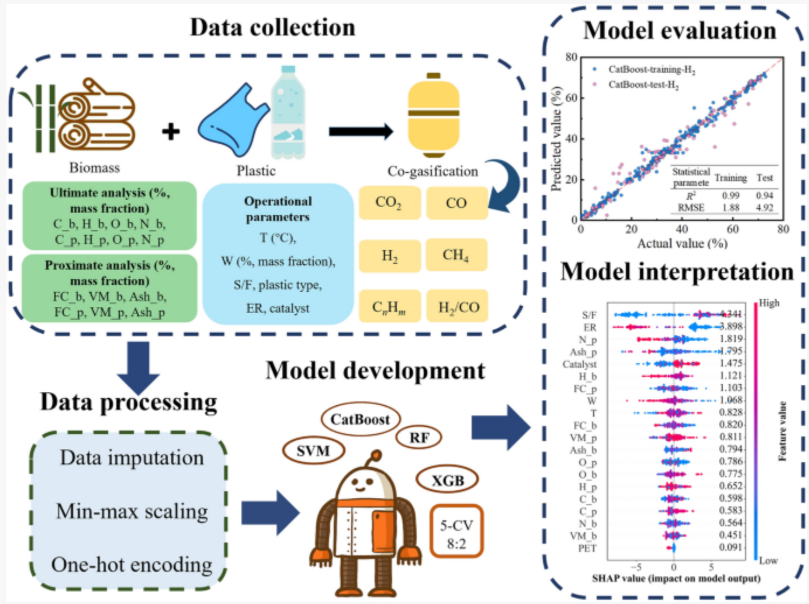
New AI framework boosts renewable syngas production efficiency

GA, UNITED STATES, December 4, 2025 /EINPresswire.com/ -- Producing clean syngas from biomass and plastic waste offers a promising route toward sustainable energy, but the underlying thermochemical processes are highly complex and difficult to optimize. The study introduces an interpretable machine learning framework capable of accurately predicting the yields of major syngas components and the H_2/CO ratio during co-gasification. By analyzing the influence of feedstock composition and operating parameters, the model identifies key factors controlling product distribution and provides mechanistic insights into the reaction system. The findings support improved syngas quality, reduced experimental workload, and more efficient process optimization, offering practical guidance for renewable fuel production and waste utilization.



Interpretable Machine Learning Framework for Biomass–Plastic Co-gasification.

Syngas, a mixture mainly consisting of CO, H_2, CH_4, CO_2, and light hydrocarbons (C2-C4), is a vital intermediate for power generation and chemical synthesis. Gasification of biomass has been recognized as an alternative to fossil fuel-based energy, while increasing plastic waste has prompted interest in co-processing biomass and plastics to enhance hydrogen yield and reduce tar formation. However, experimental co-gasification remains time-consuming and limited by variable feedstock properties and multiple operating parameters. These challenges complicate mechanistic understanding and hinder systematic optimization. Based on these challenges, there is a critical need to develop predictive and interpretable tools to guide co-gasification design and operational control.

Researchers from Hainan University and Tianjin University reported a new interpretable machine learning framework capable of predicting syngas composition during biomass-plastic co-gasification. The study was published in Waste Disposal & Sustainable Energy in 2025. The team evaluated four machine learning models and found that CatBoost achieved the highest predictive accuracy. They further applied Shapley additive explanations (SHAP) analysis to reveal how key variables, including temperature, steam-to-fuel ratio, and biomass proportion, influence syngas yield distributions.

The researchers compiled a dataset of 380 experimental data points covering multiple biomass types and three common plastics (Polyethylene, PE; Polyethylene terephthalate, PET; and Polystyrene, PS). The dataset included 20 input variables, such as elemental composition, proximate analysis, temperature, steam/fuel ratio, and equivalence ratio. Four machine learning models—CatBoost, Random Forest, Support Vector Machine, and XGBoost—were trained and compared. CatBoost exhibited the best performance, achieving R^2 values of 0.80–0.94 on the test set across major syngas components.

To enhance interpretability, SHAP analysis was used to quantify the contribution of each feature to model predictions. Temperature and steam/fuel ratio were identified as the most influential operational parameters. High temperatures promoted the conversion of CH_4 and CO_2 to CO and H_2, while increased steam raised H_2 but suppressed CO. Biomass proportion significantly affected carbon conversion, increasing CO_2 while reducing light hydrocarbons and lowering the H_2/CO ratio. Interestingly, the ash content of plastics emerged as a strong proxy variable reflecting key physicochemical characteristics that shape syngas composition.

These insights offer practical guidance for feedstock blending, operating condition selection, and catalyst-free optimization strategies.

"The combination of machine learning with interpretable analysis tools provides a new pathway to decode complex reaction behaviors in biomass-plastic co-gasification," the authors noted. "Rather than replacing experiments entirely, this framework supports targeted design and more efficient testing by identifying which variables matter most. It represents a step forward in data-driven clean energy research."

This framework enables researchers and industry engineers to optimize syngas production without exhaustive trial-and-error experimentation. The model can guide the selection of biomass-plastic blends that maximize hydrogen yield and reduce tar formation, advancing cleaner fuels and waste-to-energy conversion. The approach may also be extended to other thermochemical systems where complex feedstock-reaction interactions exist. As countries move toward carbon-neutral energy targets, the integration of machine learning into renewable fuel production pipelines may play an increasingly central role in accelerating sustainable technology deployment.

References
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