

Review of machine learning applications for predicting the quality of biomass briquettes for sustainable and low-carbon energy solutions



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ARTICLE INFO

Keywords:

Machine learning
Briquettes
Sustainable energy
Low-carbon solutions
Agricultural waste
Municipal waste

ABSTRACT

This review discusses how Machine Learning has been applied to predict the quality of biomass briquettes produced from agricultural and municipal solid organic waste, which are crucial for advancing green and low-carbon energy solutions. Traditional methods of assessment of briquette quality involve destructive laboratory experiments, do not favor sample reuse, are time-consuming, and labor-intensive, posing barriers to efficient production. This paper reviews literature on various Machine Learning models applied for predicting and optimizing briquette quality parameters, including combustion, physical, and emission properties. Several Machine Learning models have shown promising results in predicting and optimizing these key parameters for example, a Random Forest model with R^2 of 0.9936 in deformation energy prediction and Artificial Neural Networks with R^2 of 0.8936 in the prediction of impact resistance. By enhancing the accuracy and efficiency of briquette quality predictions, Machine Learning algorithms contribute to the development of high-quality biomass briquettes, thereby creating sustainable and low-carbon energy systems. This review points to critical literature gaps regarding model generalizability across diverse biomass feedstocks and integration of broader quality parameters. Addressing these gaps will advance AI-based solutions, promote greener energy practices, and support sustainable development. The findings are intended to aid researchers, industry professionals, and policymakers in advancing the production of high-quality biomass briquettes for cleaner energy and sustainable development.

1. Introduction

The reliance on fossil fuels for energy is causing a climate crisis as more energy is used and energy reserves deplete contributing to increased carbon emissions and an impending energy shortage. To address these challenges, the transition to renewable energy has become essential, where biomass amongst the alternative sources is an energy carrier of prime importance. Biomass provides a sustainable and carbon-neutral alternative by harnessing organic materials that can be replenished, and it produces lower net emissions compared to fossil fuels. Biomass, including a wide array of organic materials such as firewood, forest residues, agricultural waste, and animal dung (Ferguson, 2012) has long been used as a source of

energy. Biomass fuels contribute 96% of all renewable heat produced globally (WorldBioenergyAssociation, 2022). Its versatility in being converted into solid, liquid, and gaseous fuels makes it a prime energy carrier, capable of substituting fossil fuels (Marreiro et al., 2021). Moreover, biomass uniquely stores fixed carbon and remains cost-effective while reducing carbon dioxide (CO₂) emissions. These attributes have led researchers to project that biomass will dominate as a leading renewable energy source in the future (Kabas et al., 2024).

However, despite its advantages, utilizing raw biomass as an energy source presents significant logistical and efficiency challenges. These stem from the inherent variability in biomass materials, including differences in shape, size, and composition, complicating handling,

This article is part of a special issue entitled: AI for Sustainability published in Green Energy and Resources.

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<https://doi.org/10.1016/j.gerr.2025.100130>

Received 27 November 2024; Received in revised form 15 January 2025; Accepted 6 May 2025

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transportation, and storage processes (Kocer et al., 2023; Okot et al., 2018). The low bulk density of raw biomass further exacerbates these challenges, increasing transportation and storage costs and hindering its economic viability, which may limit its potential as a sustainable, low-carbon energy option. To mitigate these issues, biomass densification, specifically the conversion of agricultural and municipal organic solid waste into briquettes offers a promising solution. Briquettes are compact solid fuels with dimensions ranging from 10 to 200 mm in diameter and 16–400 mm in length, making them suitable for agricultural residues with varied moisture content and particle sizes (Okot et al., 2018). This flexibility reduces energy demands for drying and grinding, making briquetting an energy-efficient and cost-effective densification approach (Mani et al., 2004; Okot et al., 2018; Oladeji and Enweremadu, 2013). Agricultural and municipal organic solid wastes provide abundant feedstock for biomass briquettes, offering a dual benefit of renewable energy generation and sustainable waste management. Annually, approximately 1300 million tons of agricultural waste (Alan and Köker, 2023) and 2.01 billion tons of municipal waste are produced, with 33% of the latter unsustainably managed (World Bank, 2023). By converting such residues—ranging from food waste to agricultural byproducts such as rice husks and corn stover—into briquettes, it becomes possible to reduce waste, minimize greenhouse gas emissions, and support a circular economy (Okot et al., 2019). This strategy not only prevents methane emissions from landfills but also offers clean-burning renewable energy, significantly contributing to global decarbonization efforts. Moreover, carbonized briquettes have been shown to reduce indoor air pollution, with significant health benefits such as decreasing childhood pneumonia-related deaths by over 50% in regions heavily reliant on traditional biomass (Asamoah et al., 2016).

Agricultural and municipal organic solid wastes provide abundant feedstock for biomass briquettes, offering a dual benefit of renewable energy generation and sustainable waste management. Annually, approximately 1300 million tons of agricultural waste (Alan and Köker, 2023) and 2.01 billion tons of municipal waste are produced, with 33% of the latter unsustainably managed (World Bank, 2023). By converting such residues ranging from food waste to agricultural by-products such as rice husks and corn stover into briquettes, it becomes possible to reduce waste, minimize greenhouse gas emissions, and support a circular economy (Okot et al., 2019). Moreover, carbonized briquettes have been shown to reduce indoor air pollution, with significant health benefits such as decreasing childhood pneumonia-related deaths by over 50% in regions heavily reliant on traditional biomass (Asamoah et al., 2016).

The quality of biomass briquettes directly impacts their combustion efficiency, emissions, and overall environmental performance, which are influenced by factors such as biomass composition, processing parameters, and physical properties (Kpalo et al., 2020). Key quality parameters include the calorific value, density, compressive strength, and durability, which influence the efficiency and environmental impact of the briquettes (Kpalo et al., 2020). Traditional methods for assessing briquette quality often involve destructive testing, which is time-consuming, labor-intensive, and expensive (Kocer et al., 2023). These limitations have spurred interest in using machine learning (ML) to revolutionize the prediction and optimization of biomass briquette quality. ML enables the analysis of large datasets in real time, identifying complex patterns and correlations that may be challenging to discern using conventional approaches. By leveraging historical data and integrating multiple variables, ML algorithms can provide fast, non-destructive, and accurate predictions of briquette properties (Ascher et al., 2022).

Unlike theoretical models that rely heavily on proximate or ultimate analysis data specific to particular biomass types (Oladeji and Enweremadu, 2013), ML methods excel in handling nonlinear relationships and diverse datasets, making them highly adaptable across different biomass sources and compositions. For instance, ML can predict key quality parameters such as compressive strength, density, and calorific value by analysing input features such as moisture content, particle size, and processing conditions.

One of the key advantages of integrating ML into briquette production is its ability to optimize processing conditions based on extensive datasets, which consider the variability of different feedstocks and the mixing ratios of various biomass types. By analysing these datasets, ML models can help determine the ideal combinations of feedstock materials and adjust parameters such as temperature, pressure, and moisture content, leading to improved consistency and quality of the final briquette product (Kumar et al., 2021). This addresses a significant challenge in biomass briquette production: the variability in feedstock properties and the need to find the optimal mixing ratios that ensure both high quality and efficiency in the production process (Ali et al., 2023).

Moreover, ML's ability to generalize across various biomass sources and mixing ratios supports the development of versatile models that can adapt to different input materials and operational settings. This flexibility enhances the scalability of biomass briquette production, making it more efficient and sustainable while helping to develop high-performance briquettes with optimized energy and environmental characteristics. Whereas ML sees wide usage in the renewable energy sector in general, only a few studies have been conducted in the literature on the prediction of biomass briquette quality using ML (Saptadi et al., 2023a). Nonetheless, emerging research demonstrates its potential to bridge this gap. For example, algorithms like artificial neural networks (ANNs), adaptive neuro-fuzzy inference systems (ANFIS), and gradient-boosting techniques have shown promise in predicting briquette properties with high accuracy, as they can model complex interactions between input variables and output parameters (Bamisaye et al., 2023; Kocer et al., 2023).

This review aims to explore the applications of machine learning in predicting and optimizing biomass briquette quality, emphasizing its role in advancing green energy practices and supporting the transition to low-carbon energy systems. The paper looks into the most commonly used ML techniques, the quality parameters predicted, and their effectiveness based on reported metrics. By analysing current literature, the review highlights gaps and provides recommendations for future research to maximize the potential of ML in biomass briquette production. By enhancing biomass briquette production, ML directly supports global decarbonization efforts and the transition to green energy. Furthermore, ML-driven optimization supports economic and health improvements by promoting cost-effective and clean-burning fuel alternatives. The present review draws on insights and provides recommendations as to how machine learning can be used to further biomass briquette research and production in support of the general quest for a low-carbon future.

2. Materials and methods

This methodology identifies the potential of using machine learning in the prediction of the quality of biomass briquettes produced from agricultural residues and municipal solid organic waste. Literature was reviewed to identify existing research on this topic. An online literature searches from scientific databases including Scopus and Web of Science was conducted for the period from January 1, 2014 to 2024. Some of these keywords were combined as appropriate: "biomass briquettes", "biomass briquetting", "machine learning", "quality prediction", "agricultural waste", "municipal solid organic waste", "Emissions", "Artificial Neural Network", "Random Forest", "Extra Trees" and "Combustion". The inclusion criteria were studies published in English or with English translations and those specifically concerning the use of machine learning algorithms to forecast the quality of biomass briquettes made from agricultural waste or municipal solid organic waste. Exclusion criteria removed studies specifically on non-biomass briquettes like coal, those with no element of machine learning, and works irrelevant to quality prediction. First, there was screening for the title and abstract to include potentially relevant studies. Following this was the full-text article assessment that checked on the inclusion criteria. Moreover, reference lists of relevant articles were scrutinized during the review process in search of other relevant studies (See Table 5).

In this respect, data extraction and analysis were carried out on the

selected studies. Of importance were data related to the machine learning techniques used, the type of biomass wastes studied; quality parameters that the machine learning models targeted, like calorific value, density, and durability; data preprocessing techniques used to set the data for machine learning analysis; and metrics used in assessing model performance, like RMSE, MAE, and R-squared. The data extracted was subsequently analyzed systematically for trends and patterns in applying machine learning to predict the quality parameters of biomass briquettes. Results are then presented clearly and concisely by tables summarizing the key features of the study (See Table 5 and Table 7) and through figures showing the distribution of machine learning techniques and quality parameters (Figs. 2 and 3). This review highlights the status of the current applications of ML in biomass briquette production and identifies where more research efforts are needed to be done for green energy solutions. This review explores such applications to support the in-depth integration of advanced technologies into sustainable energy practices.

3. Predicting biomass briquette quality with machine learning

3.1. Quality of biomass briquettes

To enhance the contribution of biomass briquettes to low-carbon energy systems and sustainable waste management, it is crucial to optimize their quality. Their quality depends on raw material characteristics and production parameters. High-quality briquettes exhibit superior combustion, mechanical stability, and minimal environmental impact (Kpalo et al., 2020). Machine learning (ML) enhances this optimization by analyzing complex relationships between raw material properties and briquette performance. ML models predict quality metrics, optimize production parameters, and identify patterns in feedstock properties, enabling efficient and scalable production (Kocer et al., 2023). This integration supports sustainable energy goals by improving briquette performance and reducing emissions.

3.1.1. Effect of proximate characteristics of biomass on briquette quality

The characteristics of the biomass feedstock used in briquette production including the Moisture Content (MC), Volatile Matter (VM) Ash Content (AC), and Fixed Carbon (FC) of the feedstock determine briquette quality and burning efficiency (Asamoah et al., 2016) as shown in Table 1. By leveraging ML, the relationship between these properties and briquette performance can be optimized, supporting cleaner and more sustainable energy systems. A study by Resende et al. (2022) used

Table 1

The Proximate and Ultimate Properties of Biomass and their impact on Biomass briquette quality.

Biomass Properties	Effect on Briquette Quality and Contribution to Low-Carbon/Sustainable Goals
Moisture Content	High moisture content negatively affects combustion efficiency, increases smoke production, and reduces energy output (Saeed et al., 2021).
Fixed Carbon Content	High FC content provides longer burn time and stronger briquettes (Kebede et al., 2022).
Volatile Matter	Optimizing volatile matter improves combustion efficiency (Kebede et al., 2022) and lowers greenhouse gas emissions.
Ash Content	High ash content leads to inefficient combustion, stove corrosion, and reduced energy output (Asamoah et al., 2016).
Oxygen Content	High oxygen content reduces energy density by lowering high-energy C-H bonds (Eling et al., 2024). Reducing oxygen increases energy output
Carbon Content	Balancing carbon levels leads to efficient combustion while minimizing harmful emissions (Kimutai and Kimutai, 2019).
Hydrogen	Hydrogen content affects flame stability and combustion efficiency (Habib et al., 2024).
Nitrogen	Excess nitrogen can cause the release of toxic nitrogen oxides (NO _x) during combustion (Guo et al., 2020). Reducing nitrogen levels helps minimize harmful emissions, contributing to better air quality.

proximate, ultimate, and chemical properties of biomass materials like sugarcane bagasse and coffee residues, applying ANN and multivariate models to predict bulk density, durability, and calorific value. Similarly, Bamisaye et al. (2024a) employed proximate analysis with ANFIS to predict the calorific value of watermelon rinds and cassava crumbs, focusing on optimizing the energy content of the biomass. Table 1 summarizes the impact of these biomass properties on briquette quality and their contribution to sustainable, low-carbon energy systems.

3.1.2. Effect of the biomass elements on the quality of briquettes

The ultimate analysis is also used to quantify elements contained in the feedstock. These properties include the Carbon (C), Hydrogen (H), Oxygen (O), Sulphur (S), and Nitrogen (N) (Pilusa et al., 2013) composition of the biomass feedstock. These elements have a direct influence on how the briquettes burn influencing the type and amount of pollutants released and the calorific value of the briquette as well as shown in Table 1.

3.1.3. Effect of biomass chemical composition on the quality of briquette

The chemical makeup of each biomass source affects its bonding characteristics and hence quality (Okot et al., 2019). This chemical content of biomass comprises components like cellulose, hemicelluloses, lignin, Lignocellulose and protein, starch, crude fiber, fat, and ash extracts (Kakooza, 2014). On average, the mass ratios for cellulose, hemicellulose, and lignin in biomass are 3:2:1 (Mansora et al., 2019). When compressed and heated, proteins and starches in the biomass soften and act like glue, binding particles together to form a strong solid briquette. Furthermore, high temperatures and pressures soften lignin which acts as a glue hence improving the binding features of the biomass (Kakooza, 2014).

Machine learning models have been applied to optimize these properties. For example, Resende et al. (2022) used these models to predict key parameters like bulk density and calorific value based on the proximate, ultimate, and chemical properties of feedstocks such as sugarcane bagasse and coffee residues, contributing to more efficient, sustainable briquette production. Optimizing chemical properties boosts biomass briquette quality and supports green energy.

3.1.4. Densification process parameters and their effect on biomass briquette quality

Biomass briquette densification is a very important means to improve energy use efficiency and reduce carbon emissions, which is the main route toward sustainable, low-carbon energy systems. Table 2 shows a summary of the briquette production process parameters, including pressure, temperature, moisture content, time of pressing, particle size, and binder, and their influence on briquette quality and how their optimization contributes to the low-carbon transition.

The densification pressure enables an increase in the density of the briquettes and their mechanical stability, hence the durability of briquettes during transportation and storage, preventing them from breaking (Obi et al., 2022). For instance, studies like (Kocer et al., 2023), using Extra Trees, Random Forest, and Light Gradient Boosting for groundnut shells, demonstrated that optimizing pressure enhances compressive resistance and stability, minimizing material degradation and energy losses during transportation. Temperature, on the other hand, affects lignin softening (Okot et al., 2019), hence better cohesion of particles, better combustion, and fewer emissions. In the study of Resende et al. (2022), ANN and multivariate statistical models are used on sugarcane bagasse, coffee residues, and charcoal fines, demonstrating that optimizing temperature improves bulk density and calorific value.

In addition, optimal moisture content ensures the activation of natural binders such as lignin, improving the density, durability, and compressive strength of the briquettes (Obi et al., 2022). For example, Kabas et al. (2024) applied Random Forest and Extreme Gradient Boosting to predict deformation energy in peanut shells, showing that proper moisture content enhances briquette quality and reduces drying

Table 2
Densification process parameters and biomass briquette quality.

Parameter	Effect on Briquette Quality	Impact on Low-Carbon Transition
Pressure	Increases density and mechanical stability, minimizing the cost of transport and storage (Obi et al., 2022).	Enhances energy efficiency by minimizing emissions per unit volume of fuel transported and consumed, which is essential for low-carbon energy goals.
Temperature	Softens lignin, which acts as a natural binder, improving particle cohesion (Okot et al., 2019).	Improved strength reduces the likelihood of briquette breakage, leading to more efficient combustion (Obi et al., 2022). Enhanced combustion efficiency reduces incomplete combustion, which in turn decreases carbon emissions per unit of energy produced.
Moisture Content	Ensures binder activation; too much or too little moisture weakens briquettes (Obi et al., 2022).	Optimization of moisture reduces drying energy requirements and enhances combustion efficiency, lowering the carbon footprint of the production process.
Pressing Time	Improves compaction and durability, though excessive pressing time increases energy consumption (Musabbikhah et al., 2022).	Optimizing pressing time is essential to balance product quality with production energy use, supporting low-carbon manufacturing processes.
Particle Size	Smaller particles enhance bonding, resulting in stronger briquettes, though very fine particles increase processing energy (Mani et al., 2004).	Optimization minimizes energy input while maintaining product strength, promoting energy-efficient and low-carbon industrial practices.
Binder & Binder Ratio	Binders (e.g., starch, clay) improve particle cohesion and mechanical strength, but excessive binder use may reduce energy density (Obi et al., 2017).	Sustainable, plant-based, or organic binders minimize reliance on synthetic materials and reduce the carbon intensity of the production process, supporting green engineering approaches.

energy requirements. Adequate pressing time ensures proper compaction, resulting in denser and more durable briquettes (Musabbikhah et al., 2022). MLP-ANN models (Kumar et al., 2021) demonstrated how pressing time influences density and impact resistance in millet bran briquettes, highlighting the need for optimization to balance quality and energy consumption. Using MOGA-ANN for sawdust, sugarcane bagasse, and paddy straw (Ali et al., 2024), it was showed that particle size affects bonding; smaller particles enhance bonding but require more energy to process.

Lastly, binders and their ratios are significant in influencing the mechanical strength and cohesion of the biomass briquettes (Obi et al., 2022; Olugbade et al., 2019). Excessive use of binders results in less energy density of the briquettes and increases the cost of production. ANN and CNN for coconut shell, wood, and adhesive (Saptadi et al., 2023b) illustrated how binder optimization affects briquette composition. Machine learning (ML) can analyze data to identify optimal combinations of these factors, ensuring energy-efficient, low-emission briquettes for sustainable renewable energy.

3.1.5. Physical quality parameters of biomass briquettes

Some of the physical properties for the biomass briquettes include durability, impact resistance, density, and compressive strength (Muntean, 2020). These have a highly significant influence on the quality and handling characteristics of the briquettes and are directly correlated with the important parameters in the briquette densification process, such as pressure, temperature, particle size, and binder type (Yank et al., 2016). Optimizing these physical properties contributes to the overall

efficiency and sustainability of biomass briquettes in green energy systems.

3.1.5.1. Durability. The durability of a briquette measures its resistance to actions resulting from handling and transportation including but not limited to vibrations, falls, and scratches. Superior durability guarantees briquettes remain intact throughout storage and transit, thereby reducing the amount of dust and waste produced (Okot et al., 2018). A durability of 80% and above is recommended for good-quality briquettes, promoting consistent energy output and minimal losses during their lifecycle (Obi et al., 2017). Machine learning models such as Random Forest and ANN have been used to predict deformation energy and durability (Florica et al., 2023; Kabas et al., 2024).

3.1.5.2. Density. Density, the mass per unit volume, is a key property of biomass briquettes, influencing storage, transportation, and energy efficiency. It is assessed as compressed density (immediate post-densification), relaxed density (post-settling), and bulk density (mass-to-volume ratio of multiple briquettes, including gaps). Higher densities, ranging from 0.6 to 0.9 g/cm³ (ISO, 2014), improve energy output and reduce transportation costs, supporting sustainable energy goals by minimizing carbon footprints. Machine learning (ML) tools have been utilized to optimize density. For example, Kumar et al. (2021) employed MLP-ANN to predict density, durability, and impact resistance of millet bran briquettes using inputs like moisture content, temperature, and applied pressure. This demonstrates how ML enhances briquette quality and efficiency in green energy systems.

3.1.5.3. Compressive strength. A briquette's compressive strength is its ability to resist crushing under pressure. It measures how much weight the briquette can handle until it breaks. The compressive strength predicts how well briquettes will hold up under weight from other briquettes stacked on them when stored, handled, or transported (Okot et al., 2018). The guiding value of compressive strength is 1.0 MPa, and measurements are typically carried out using standard methods such as ASTM D2166-85 (ASTM International, 2008).

3.1.6. Combustion properties of biomass briquettes

Biomass briquettes also have combustion characteristics that affect their quality. These include the ignition time, burning time, burning rate, and calorific value as shown in Table 3. The biomass properties and briquetting conditions like the particle size, binder, and pressure influence these combustion properties. For example, Kimutai and Kimutai (2019) reported a calorific value of 30.5 MJkg⁻¹ for cashew nut briquettes containing 30% cassava binder as opposed to 28.3 MJkg⁻¹ in binder-less briquettes. Bamsaye et al. (2023) used LMBP-ANN and FCM-ANFIS models to predict the calorific value of briquettes made from alkaline-treated and untreated *Celosia argentea*, finding a positive

Table 3
The combustion properties of biomass briquettes.

Combustion Property	Explanation
Burning rate	The pace at which a specific mass of fuel burns in air. A well-balanced burning rate ensures consistent energy release and can help optimize fuel use while minimizing emissions (Abdulkareem et al., 2018; Achebe et al., 2018).
Ignition time	The amount of time required for the briquette to ignite when moderate amounts of extra fuel, such as kerosene or gas, are used (Elsisi et al., 2023). Reduced ignition time enhances ease of use and supports clean energy systems.
Burning Time	It is the amount of time from the beginning of combustion to the is complete combustion of biomass briquette burned (Achebe et al., 2018). Longer burning time improves fuel efficiency.
Calorific Value (Heating Value)	Heating value, a measure of energy content per unit mass (Ngusale et al., 2021). Higher calorific values indicate greater energy efficiency and a lower carbon footprint.

Table 4
Non exhaustive List of Potential Emissions from Biomass Combustion.

Emission	Hazard	limit	Standard
CO (ppm)	Can lead to health issues	50	OSHA
CO ₂ (ppm)	Contributes to global climate change	5000	OSHA
NO _x (ppm)	Contribute to air pollution and acid rain	20	OSHA
PM _{2.5} (µg/m ³)	Air pollution and health Hazards	35	EPA

correlation between moisture content, fixed carbon, and volatile matter. Similarly, [Resende et al. \(2022\)](#) applied ANN and multivariate statistical models to predict the net calorific value of briquettes made from sugarcane bagasse, coffee residues, and charcoal fines, based on proximate and ultimate chemical properties.

A burning rate of 9.416 g/min for the 30% cassava binder sample was reported as opposed to the 7.436g/min¹ of the 10% cassava binder sample briquette ([Kimutai and Kimutai, 2019](#)). Higher compaction pressure in briquettes reduces pore spaces, increasing ignition time. Sawdust briquettes at 420.4 kN/m² ignited in 1.28 min, while rice husk briquettes at 630.6 kN/m² took 1.58 min ([Aliyu et al., 2021](#)). However, studies predicting burning rate, burning time, or ignition time using machine learning are currently lacking, indicating a significant research gap that needs further investigation.

3.1.7. Emission characteristics of biomass briquettes

Briquette emissions, driven by biomass, binders, and additives, impact air quality and health. Harmful pollutants released during the combustion of biomass include particulate matter, carbon monoxide (CO), hydrocarbons, NO_x, and SO_x, whose effects are severe ([Monteiro et al., 2024](#)). Managing emissions is crucial for biomass briquettes to support low-carbon energy, with limits set by the Occupational Safety and Health Agency ([OSHA, 2024](#); [Elsisi et al., 2023](#)) and the upper limit exposure for PM_{2.5} provided by the Environmental Protection Agency ([EPA, 2012](#) (see [Table 4](#))). Machine learning (ML) tools can optimize briquette properties to reduce emissions. However, direct ML studies targeting emission prediction and optimization remain limited, highlighting a critical area for future research.

3.2. Predicting biomass briquette quality with machine learning

The production of biomass briquettes involves a complex interplay of various physical, chemical, and combustion-related parameters. These factors, including density, moisture content, and calorific value, must be optimized to produce high-quality briquettes with efficient combustion and low emissions. Machine Learning (ML) provides a non-destructive method for biomass briquette quality prediction by analyzing and drawing complex trends in large datasets ([Oladeji and Enweremadu, 2013](#)) to find relationships between input materials and desired ([Afolabi et al., 2022](#); [Kocer et al., 2023](#)). ML has been widely used in the renewable energy sector in the optimization of processes, for example, prediction of HHV of Biomass ([Afolabi et al., 2022](#); [Güleç et al., 2022](#); [Ighalo et al., 2022](#); [Kujawska et al., 2023](#)), bio char yield ([Li et al., 2012](#)), optimization of the gasification process ([Ascher et al., 2022](#); [Osintsev et al., 2021](#)) and optimization and prediction of biomass briquette quality ([Bamisaye et al., 2023](#); [Kabas et al., 2024](#); [Kocer et al., 2023](#); [Kumar et al., 2021](#); [Oladosu et al., 2023](#); [Saptadi et al., 2023b](#)). This predictive capacity contributes to improvements in the sustainability of biomass briquette production, leading to more effective resource use, reduced emissions, and energy-efficient briquettes. [Table 5](#) summarizes key studies on ML utilization for briquette quality prediction or optimization between 2014 and 2024.

3.2.1. ML approaches in Biomass Briquette Studies

Various ML techniques are applied to different aspects of biomass briquette production and quality control. With supervised Learning, during training the machine is given training data with labeled input and

Table 5
Studies on the use of Machine learning for the prediction of Biomass Briquette quality.

Feedstock	ML Tools Used	Input Parameters	Predicted Parameters	Author
Ground nut shells	10 ML models and Extra Trees, Random Forest, and Light Gradient Boosting –best	Particle size, material moisture, pressure value, density, shatter index, and tumbler index	Compressive resistance	Kocer et al. (2023)
Alkaline treated and Untreated Celosia argentea Millet Bran	LMBP-ANN and FCM- ANFIS	Ash content, moisture content, fixed carbon, and volatile matter	compressive strength and calorific value	Bamisaye et al. (2023)
Coconut shell, wood and adhesive	MLP-ANN (23 data points from literature) Artificial Neural Network (ANN) and Convolutional Neural Network (CNN).	MC, temperature, and applied pressure digital images of organic waste raw materials	Density, Durability and Impact Resistance Briquette composition	Kumar et al. (2021) Saptadi et al. (2023b)
Sugarcane bagasse, coffee residues and charcoal fines	ANN and multivariate statistical models, Clustering methods like PCA, HCA, and SOM for data analysis.	Proximate, Ultimate and chemical properties	Bulk Density, durability Net calorific value	Resende et al. (2022)
Peanut shells	Random Forest, Extreme Gradient Boosting, and CatBoost ensemble learning methods	moisture content, compression resistance, briquette density, tumbler index, water resistance, shatter index, and compression stress	Deformation Energy	Kabas et al. (2024)
Miscanthus and willow	ANN	Feedstock type Moisture content Particle size Feedstock ratio	Energy consumption, density, durability	Florica et al., (2023)
Watermelon rinds with and without sulfuric acid	neuro-fuzzy inference system (ANFIS)	Proximate Analysis	Calorific value	Bamisaye et al. (2024a)
Cassava Crumps as binder sawdust, sugarcane bagasse, and paddy straw	MOGA-ANN	Feedstock mixing ratio	Calorific Value, Ash	Ali et al. (2023)
of paddy straw, sawdust, cow dung, and paper pulp	MOGA-ANN	Feedstock ratios	Calorific value, Ash content	Ali et al. (2024)

Table 6
Different ML Algorithms and when they can be applied.

Algorithm	Strengths	When to Use in Biomass Briquette Research
Random Forest	Robust to overfitting, handles missing values well, provides feature importance	Large datasets with mixed features, interpretability important
Extra Trees	Similar to Random Forest, but often faster to train	Speed is a priority, complex datasets with interactions
XGBoost	Handles missing values, supports various objective functions, and efficient implementation	High performance is critical, structured data
LightGBM	Faster training, lower memory usage, handles large datasets	Speed and efficiency are critical, large datasets
CatBoost	Handles categorical features effectively, robust to outliers	Categorical data, imbalanced datasets
ANN (Artificial Neural Network)	Powerful for complex non-linear relationships, good at feature extraction	Large, complex datasets, and multi output regression, image recognition
ANFIS (Adaptive Neuro-Fuzzy Inference System)	Combines fuzzy logic with neural networks, handles uncertainty	Complex systems modeling, control problems

corresponding output values (Kinsley and Kukiela, 2020; Sodhi et al., 2019). A mapping function also called the model identifies the expected output for a given input generated by the SL algorithm (Kinsley and Kukiela, 2020; Sodhi et al., 2019). The model predicts outputs for test data using labeled inputs, such as biomass properties and production conditions, to evaluate briquette quality metrics like CV, density, durability, and strength. Then the outputs can be predicted for the test dataset that is provided with only input data. According to Badillo et al. (2020), the two major categorizations of SL are classification which gives categorical outputs, and regression where the output values are numerical. Some of the most common SL algorithms include K-Nearest neighbor, Decision Trees, Naïve Bayes, Linear Regression, Support Vector Machines, and Artificial Neural Networks (Sodhi et al., 2019). The categories where they belong are shown in Fig. 1. Supervised Learning has been widely used for briquettes quality prediction as shown in Table 5. Supervised learning can be categorized into Classification and regression techniques.

Classification models can be used to categorize different types of biomass using their chemical and proximate characteristics (Saptadi et al., 2023b). For example, a Convolutional Network Model (CNN) has been employed to classify the organic waste (coconut shell and wood),

Table 7
Performance of Machine Learning Models on Biomass briquette quality from Literature.

Model		R	MAPE	MAE	RMSE	MAD	Author
Extra Trees	Mean	0.7595	0.0799	284.0000	368.1200	NA	Kocer et al. (2023)
ANFIS	Train	0.9534	0.9690	NA	0.0077	0.0060	Bamisaye et al. (2023)
	Test	0.9684	1.1899	NA	0.0824	0.0678	
ANFIS	Train	0.9084	1.7531	0.2151	0.2594	0.1902	Bamisaye et al. (2024a)
	Test	0.9006	1.8443	0.2230	0.2887	0.2265	
ANFIS-FCM	Train	NA	2.1040	0.0249	0.3110	0.0257	Bamisaye et al. (2024b)
	Test	NA	1.0180	0.0223	0.0249	0.0205	
ANN	Density	0.8605	NA	NA	NA	NA	Kumar et al. (2021)
	Durability	0.7133	NA	NA	NA	NA	
	Impact Resistance	0.89362	NA	NA	NA	NA	
MLR	Density	0.6680	NA	NA	NA	NA	Kabas et al. (2024)
	Durability	0.5540	NA	NA	NA	NA	
	Impact Resistance	0.4740	NA	NA	NA	NA	
CatBoost	Train	0.9921	0.0081	6.1000	8.25	NA	Kabas et al. (2024)
Extreme Gradient Boosting		0.9991	0.0023	1.8900	2.86	NA	
Random Forest		0.9936	0.0057	4.1600	7.14	NA	Ali et al. (2024)
MOGA -ANN	Train	0.9957	NA	NA	NA	NA	
	Test	0.5531	NA	NA	NA	NA	
MOGA-ANN				35927.9648			Ali et al. (2023)

optimizing briquette formulations by forecasting the best formulations (Saptadi et al., 2023b). This approach ensures that the best raw material composition is selected, resulting in high-quality briquettes that perform better in terms of energy output and sustainability. By using CNNs to automate and enhance the classification process, there is significant error reduction in material selection, improving overall process efficiency and reducing waste (Saptadi et al., 2023b).

Regression models are particularly useful for predicting key briquette quality parameters, such as density, compressive strength, and calorific value (Bamisaye et al., 2023; Kabas et al., 2024; Kocer et al., 2023; Kumar et al., 2021; Oladosu et al., 2023; Saptadi et al., 2023b) among others as shown in Table 5. These models can be used by producers to optimize the physical, combustion efficiency, heat output, while minimizing emission levels of biomass briquettes by fine tuning biomass mixtures, binders and briquetting conditions. This ensures that the resulting briquettes are both high in energy content and low in emissions, contributing to more sustainable energy use.

Unsupervised Learning involves providing the machine with data without labels and categories. The algorithm then identifies hidden structures in this data set as per the patterns generated without any former training (Sodhi et al., 2019). Unsupervised is used for clustering and association problems and is less used for regression problems. However, with these regression problems like the prediction of the quality of biomass briquettes, Unsupervised learning techniques has been widely useful in data exploration. An example of the use of these Unsupervised Learning Algorithms in Biomass Research is the use of PCA and Hierarchical Cluster Analysis (HCA) (Resende et al., 2022). PCA was used to project the relationship between variables onto lower-dimensional spaces while HCA was applied to the grouping of samples according to their physicochemical properties during the prediction of Bulk Density, durability, and Net calorific value of biomass pellets (Resende et al., 2022) as Show in Table 5.

Reinforcement Learning (RL) teaches machines through trial-and-error and reward feedback to optimize behavior in dynamic systems (Badillo et al., 2020). While RL algorithms like Q-learning and Markov Decision Processes are effective, their use in biomass briquettes is unexplored. Training RL models can be computationally intensive, posing challenges for manual processes in developing countries due to limited data and resources.

3.2.2. Machine learning applications in biomass briquette production

Machine learning (ML) has emerged as a crucial tool in optimizing the production of biomass briquettes from agricultural and municipal solid organic waste. These briquettes serve as a sustainable and low-carbon

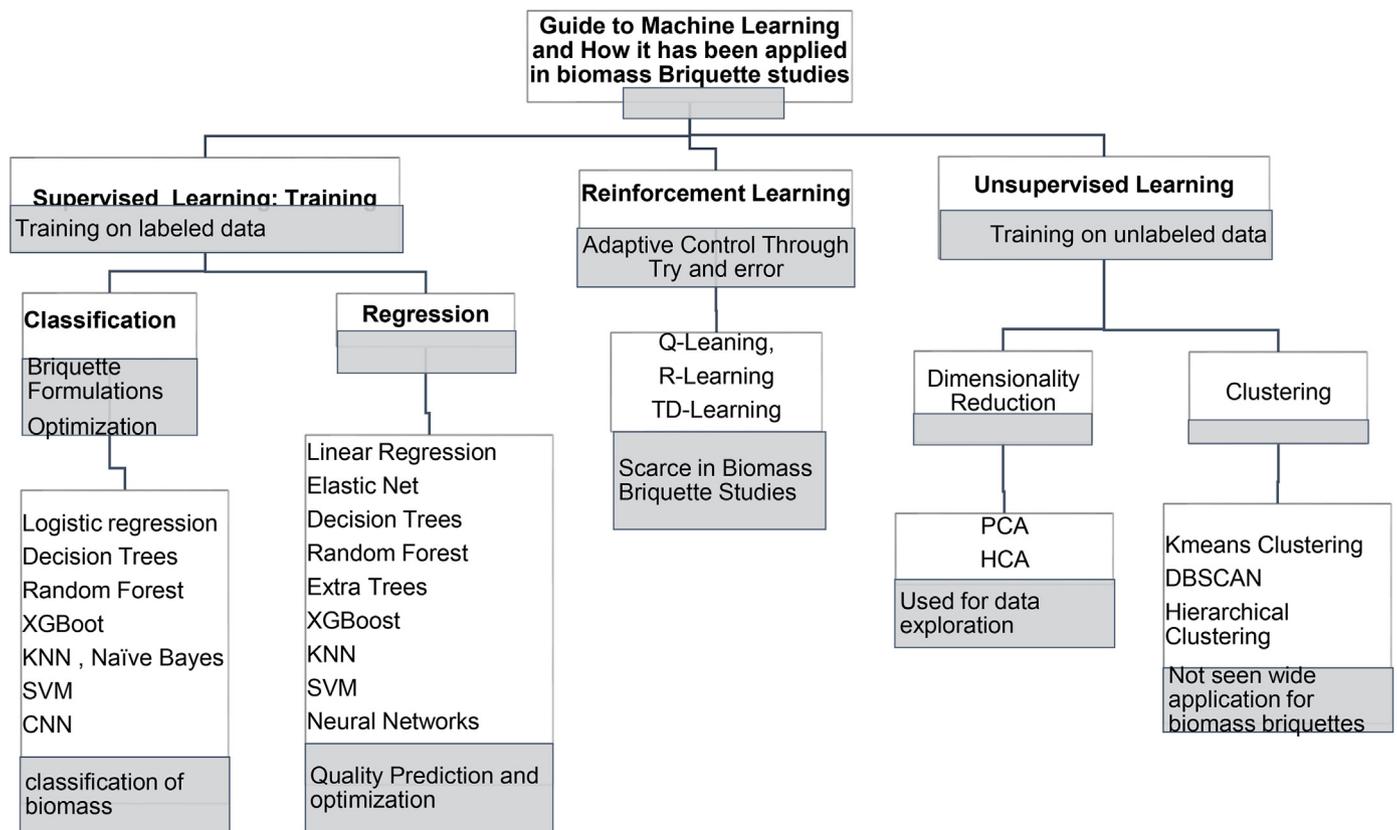


Fig. 1. Summary of Categorization of Key machine learning (ML) algorithms and How they have been used in Biomass Briquette studies.

ARTICLES ON BIOMASS BRIQUETTES AND ML

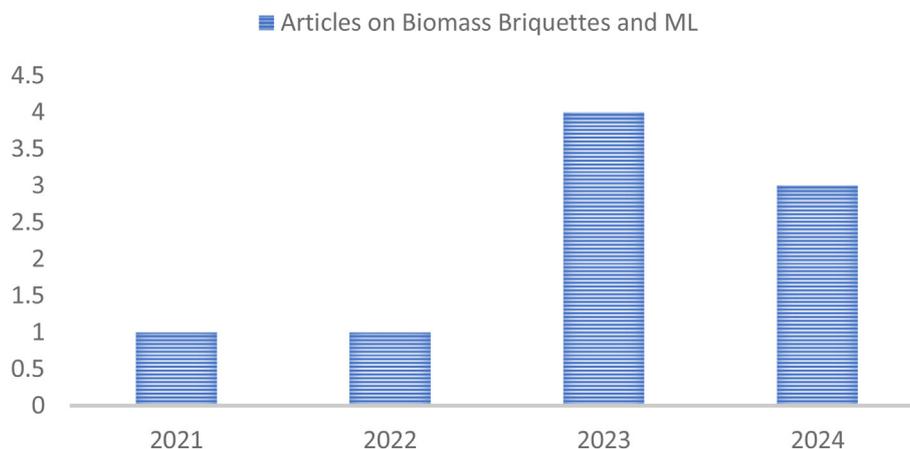


Fig. 2. Yearly distribution of articles on biomass briquettes and machine learning.

alternative to traditional fossil fuels, supporting global efforts to reduce greenhouse gas emissions. The complex nature of biomass feedstock and the variability in process conditions make traditional optimization methods insufficient (Deshannavar et al., 2018; Kujawska et al., 2023). ML provides a robust solution by predicting key quality parameters of briquettes such as density, durability, compressive strength, and heating value, improving production efficiency, and advancing low-carbon technologies.

This section reviews the use of various ML models in predicting the quality of biomass briquettes and their role in promoting sustainable energy solutions. ML algorithms including Artificial Neural Networks

(ANNs), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and ensemble learning techniques have been widely used in literature for biomass briquettes. As shown in Table 5 and Fig. 3, the predominant use of ANN underscores its effectiveness in this domain, followed closely by ANFIS, as illustrated in Fig. 3. The concentration of studies from 2021 to 2024 as shown in Fig. 2 indicates a growing interest and urgency in harnessing ML for optimizing biomass briquettes, which play a vital role in sustainable energy strategies.

3.2.3. Ensemble based methods

Machine learning models improve biomass briquette production

Model Distribution in Machine Learning Studies

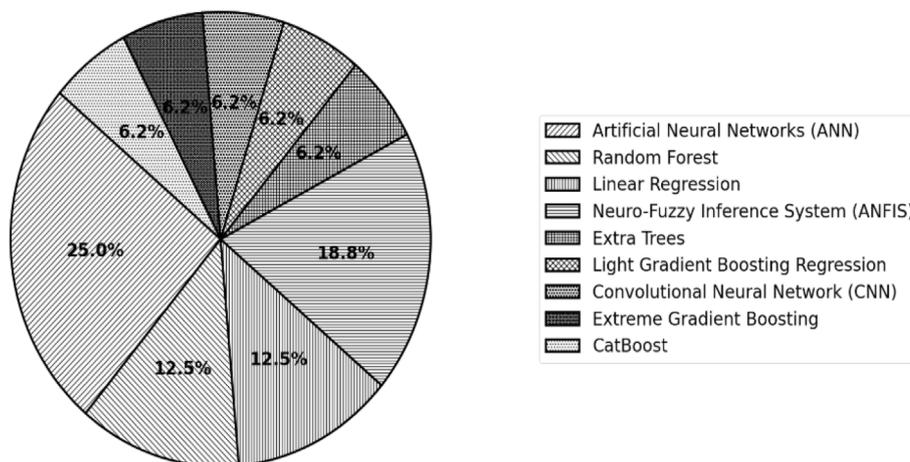


Fig. 3. Model distribution in machine learning for biomass briquette studies.

efficiency and environmental impact, paving the way for advanced techniques like ensemble learning. This approach combines multiple models into one, enhancing performance and contributing to more effective green energy solutions. In this respect, it has recently been a topic of considerable interest in machine learning research including research on biomass briquettes [Kabas et al. \(2024\)](#); [Kocer et al. \(2023\)](#).

Machine learning models have been applied to optimize biomass briquette quality for better green energy solutions. For example, a study by [Kocer et al. \(2023\)](#) compared ten algorithms to predict the compressive strength of briquettes made from groundnut shells, with Extra Trees, Random Forest, and Light Gradient Boosting performing best. The study suggested using a single model for different biomass materials, but it mainly focused on compressive resistance, leaving other quality parameters like density and durability unexplored. Including binder type and feedstock properties could improve prediction accuracy.

Similarly ([Kabas et al., 2024](#)), demonstrated the effectiveness of ensemble learning techniques including Random Forest (RF), Extreme Gradient Boosting (XGB), and CatBoost in the determination of the deformation energy for biomass briquettes made from peanut shells. Input variables included MC, Density, Specific compressive force, shatter index, compression resistance, and compression stress. Ensemble methods aggregate predictions from multiple models, leading to improved accuracy and robustness ([Kabas et al., 2024](#)). For example, Random Forest and Extra Trees were noted for their effectiveness in predicting various briquette properties, while CatBoost showed promise in handling categorical data and improving prediction performance ([Kocer et al., 2023](#)). The use of these ensemble techniques can be particularly beneficial in optimizing briquette quality, but further research is needed to assess their applicability across different biomass materials. Ensemble methods that outperformed others in comparative studies on biomass briquettes include Extra Trees ([Kocer et al., 2023](#)), Extreme Gradient Bosting and Random Forest ([Kabas et al., 2024](#)) shown in [Table 7](#). These methods are discussed in the following subsections.

3.2.3.1. Random forest algorithms. With the random forest algorithm, a forest of decision trees is created. Each tree is trained on a random subset of the original data; additional randomness is injected by randomly choosing features, and variables at every split point within the tree ([Kocer et al., 2023](#)). This process offers a general variance reduction in the model and avoids overfitting. It has been shown that to make a prediction, the Random Forest takes an average of all the outputs from individual trees ([Kabas et al., 2024](#)). Random Forest offers the following advantages that leverage it as most suitable for predicting the quality of biomass briquettes. Random Forest can model complex relationships that exist

between multiple input parameters with the desired quality outputs of briquettes, such as density and durability, even if the relationships involved are nonlinear. Since the algorithm is of an ensemble nature, it would not greatly be affected by noise and outliers in the data, hence giving out reliable predictions ([Kocer et al., 2023](#)). Random Forest models usually have high accuracy, often at efficient processing speed hence, they can be used with large data sets. In addition, it can perform dimensionality reduction ([Kocer et al., 2023](#)) and feature selection. In addition, through the Out of Bag (OOB) Error mechanism, Random Forest provides an inbuilt cross-validation mechanism, boosting model performance.

3.2.3.2. Extra Trees. Extra Trees is a relatively recent algorithm in the family of ensemble learning algorithms, constituting the strengths of Random Forest ([Kocer et al., 2023](#)). Like in Random Forest, the Extra Trees methodology also depends on a forest of decision trees. Each tree looks at a random subset of the original data, and then, at each split point of the tree, it selects features randomly. Another critical difference between Extra Trees and Random Forest is how they handle feature selection during the construction of trees. Random Forest will perform what is called best-split finding by looking for the best optimal feature and split value at each node. In contrast, Extra Trees takes a much simpler approach where it randomly selects a feature at each split point and does not bother actively searching for the best one ([Mastelini et al., 2022](#)). Extra Trees can be less inclined to overfit the data compared with Random Forest. Extra Trees adds more randomness, by not tending to find the best possible split at every node, which can be very useful in generalizing when the model encounters new data. Other advantages exist for ensemble methods like Random Forest mentioned in the previous section.

3.2.3.3. CatBoost. CatBoost comes from two words Category and Boosting ([Kabas et al., 2024](#); [Vermeulen, 2019](#)). CatBoost is a gradient-boosting algorithm specifically developed to work well with categorical data. Contrary to other methods, which need much pre-processing, CatBoost handles categorical features straightforwardly by ordered boosting. In other words, it assigns numerical values to the categories according to their target statistics without losing any valuable information. CatBoost fights overfitting with balanced trees, which distribute decision-making fairly ([Dorogush et al., 2018](#); [Kabas et al., 2024](#)). Iteratively building decision trees and correcting mistakes, CatBoost has an intrinsic ability to model complex relationships within the data, thus allowing it to achieve improved predictive performance compared to conventional gradient-boosting algorithms. It is faster than the XGB and LGBM because it has both CPU and GPU learning algorithm

implementation.

3.2.3.4. Extreme Gradient Boosting and Light Gradient Boosting Method (LightGBM). XGBoost and LightGBM are advanced gradient boosting algorithms used for improving prediction accuracy and computational efficiency. XGBoost grows trees level-wise, focusing on regularization, pruning, and parallel processing, making it popular for solving overfitting. LightGBM, in contrast, grows trees leaf-wise, enabling continuous improvement. Both are widely used for their strengths in speed and performance (Kabas et al., 2024). CatBoost, another algorithm, uses oblivious trees, where the same condition is applied for splits at each level. These differences in tree structure influence the performance and applicability of each algorithm.

The XGBoost gradient boosting algorithm builds upon some ensemble of models for sequential improvements in predictions, empowered with the most advanced techniques for regularization, tree pruning, and parallel processing in order to ensure both performance and accuracy (Kabas et al., 2024). In view of these in-built processes, XGBoost has now become popular for use in all other machine learning tasks with respect to the solution of overfitting and computational efficiency.

LightGBM is a gradient boosting framework that is designed to be speedy and efficient, but the only difference from XGBoost is that it grows trees in a leaf-wise manner rather than a level-wise manner that in XGBoost, which allows for a continuous level of improvement (Kocer et al., 2023). Further added is the technique that helps in improving the gradient-based on one-sided sampling and feature bundling. Both, XGBoost as well as LightGBM, have their own sets of strengths and are being widely used in various industries for the same reason.

In the case of XGBoost, trees are balanced and grown level by level to guarantee that branches have approximately equal depths. In contrast, LightGBM utilizes a leaf-wise growth style to grow trees into asymmetric shapes (Boldini et al., 2023). CatBoost specially builds trees at each level of a tree, it always applies the same condition for the split—so-called oblivious trees. All these differences in structure exert great influence on these algorithms' performance and effectiveness. A summary of the advantages and applicability of all the algorithms discussed is shown in Table 6.

3.2.4. Artificial neural networks (ANNs)

Artificial Neural Networks are computational models inspired by the human brain but instead of having dendrites, axons, and axon terminals ANNs have neurons, activations, and lots of connectivity (Kinsley and Kukiela, 2020) as shown in Fig. 4. The Processing units connected together, also called neurons, make up the ANNs, which are organized in layers as shown in Fig. 4. Neurons compute and work collaboratively to process information, as shown in Fig. 5. ANNs pick up learning from data by tuning their weights and biases. There is an input fed in the input layer, and it goes through a few hidden layers to produce output. Each inter-neuron connection has a weight that decides the influence it has on the following neuron, and each neuron has a bias that shifts its output (Kumar et al., 2021). All of these parameters are usually randomly initialized and then fine-tuned in the process of learning. Activation functions introduce non-linearity into a network, enabling it to pick up complex patterns (Kinsley and Kukiela, 2020). Common activation functions include sigmoid, hyperbolic tangent, and linear.

ANNs must be trained and tested before being validated for optimal performance. Probably the most popular way of training is through backpropagation where the network's weights are modified to reduce errors. The three approaches to BP include Levenberg-Marquardt, scaled conjugate gradient, and Polak-Ribiere conjugate gradient (Kumar et al., 2021). Though more computer power is required, the method of Levenberg-Marquardt is preferred due to its fast converging and stability (Kumar et al., 2021). The Levenberg-Marquardt was successfully used for model training on briquette quality prediction and optimization (Ali et al., 2023; Kumar et al., 2021).

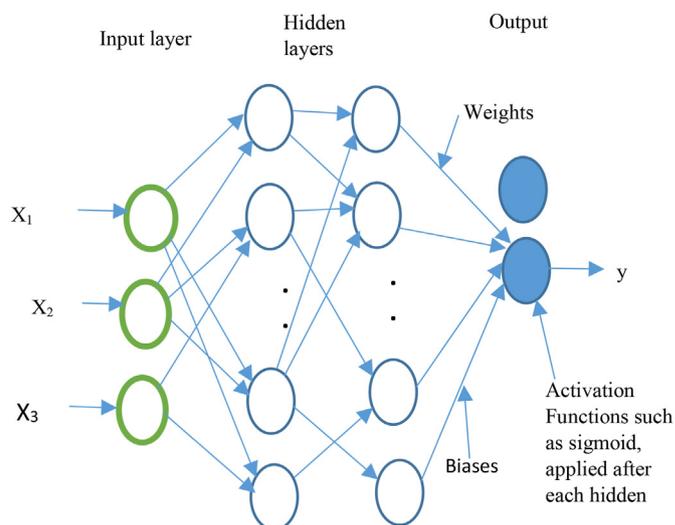


Fig. 4. Structure of an Artificial Neural Network (ANN) showing input, hidden, and output layers with neurons, weights, biases, and activation functions.

The application of ANNs in modeling can be very vital in establishing relationships between many input parameters, such as pressure, type, and ratio of binder, and composition of feedstock, with quality outputs like density, durability, burning efficiency, and emissions desirable for biomass briquettes. This is because ANNs are good at capturing complex interactions of the different factors involved, even if these variables act nonlinearly on the quality of the briquettes. ANNs are good at processing this high-dimensional data and identifying intrinsic relationships within it impacting briquette quality. One of the advantages is that ANNs do not require users to identify which of the features in a dataset are the most important; instead, the network can learn them itself through the training process, which consequently allows a much broader range of analysis throughout. However, despite their advantages ANNs also have shortcomings. It is Difficult to interpret the decision-making process of ANN, making it challenging to explain model outputs. ANNs are computationally expensive and require most amounts of data. While dealing with briquette quality predictions, the advantages of ANNs outweigh the disadvantages.

Artificial Neural Networks (ANNs) have been used in various studies to optimize biomass briquette properties due to their ability to model complex relationships between input variables and output quality parameters. For example (Resende et al., 2022), used ANN to optimize the production of sugarcane bagasse briquettes, focusing on bulk density and high heating value (HHV). A similar study (Kumar et al., 2021), used a multi-layer perceptron (MLP) neural network to predict the density, durability, and impact resistance of millet bran briquettes based on temperature and applied pressure as model inputs. Several studies have applied ANN models to forecast the HHV of biomass feedstock. HHV represents the useable energy of the biomass which must be determined before the densification of biomass for energy. ANN has been used to predict the HHV of biomass feedstock using proximate analysis data (Kujawska et al., 2023; Uzun et al., 2017) as well as using both proximate and ultimate analysis data (Afolabi et al., 2022; Ighalo et al., 2022). The predictive power of these models enables more accurate control over production variables, resulting in higher-quality briquettes and reduced environmental impact.

While these studies demonstrated effective predictions, there is a need for a unified ANN model that simultaneously forecasts high heating value (HHV), combustion characteristics, and physical properties. Moreover, assessing the generalizability of ANN models across various biomass feedstocks, particularly from agricultural and municipal waste, remains a key challenge for achieving broader sustainability goals.

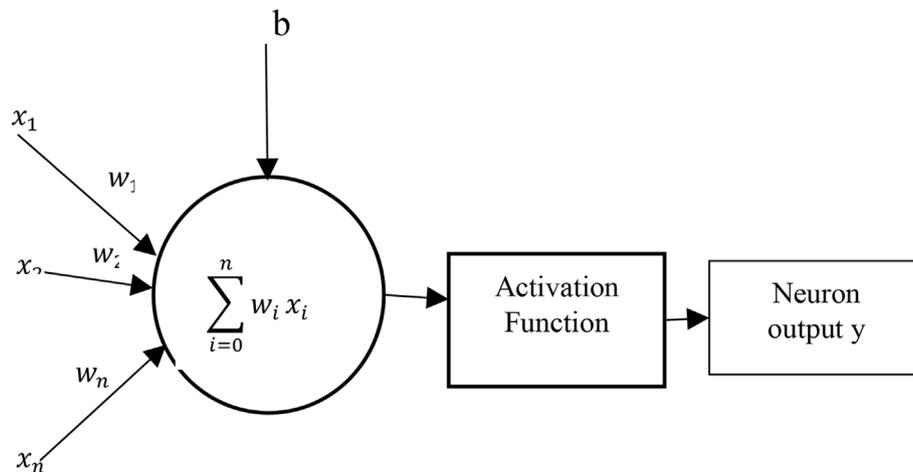


Fig. 5. Basic structure of an artificial neuron showing weighted inputs, bias, activation function, and output.

3.2.5. Adaptive neuro-fuzzy inference systems (ANFIS)

ANFIS is a very powerful computational model that synergistically integrates the benefits neural networks and fuzzy logic (Bamisaye et al., 2023), making it adept at handling the uncertainties and non-linearities inherent in biomass briquette production.

The architecture for ANFIS involves five layers: input, rule-based, defuzzification, output, and fuzzification shown in Fig. 6. Membership functions transform input signals into fuzzy sets. Afterwards, the fuzzy sets are combined by the product rule into firing strengths in the rule-based layer. A clear result is produced in the defuzzification layer (Bamisaye et al., 2024a). The final output is then a weighted total of the individual outputs.

The fuzzy logic in ANFIS provides interpretability meaning that one can see why a model makes certain decisions. Due to its ability to handle uncertainty, ANFIS can effectively handle noisy and incomplete data, enabling accurate classification and regression predictions. It finds an important application in those areas where human expertise is allowable to be combined with data-driven optimization. The problems of ANFIS models are related to the large number of inputs, which, being exponentially related to rules, imply high complexity in the management of membership functions. This complexity contrasts with neural networks, which handle large datasets and high-dimensional input spaces more efficiently (Kumar et al., 2021). In a study by (Bamisaye et al., 2023), ANFIS outperformed the Levenberg Marquardt Backpropagation-based ANN (LMBP-ANN) in the determination of the compressive strength and calorific value of biomass briquettes from alkaline-treated and Untreated *Celosia argentea*, showcasing its effectiveness in handling complex biomass characteristics and improving briquette quality.

3.2.6. Multi-objective genetic algorithm combined with artificial neural Networks (MOGA-ANN)

The MOGA-ANN represents an advanced approach to optimizing multiple objectives in biomass briquette production. This method optimizes neural network architectures and parameters with a genetic algorithm to address multiple objectives simultaneously (Ali et al., 2023). The flexible adjustment of the neural network structure to fit any problem presented makes this approach very powerful; it is applied to tasks like Hyperparameter optimization, model selection, and trade-off analyses. For the case of biomass briquettes, MOGA ANN can simultaneously optimize multiple key parameters, such as maximizing Calorific Value and lowering ash content (Ali et al., 2024). This capability is particularly valuable for enhancing the quality and sustainability of biomass briquettes, as it allows for a comprehensive evaluation of production trade-offs and optimization of multiple performance metrics.

However, despite its powerful capabilities, MOGA-ANN has some drawbacks. MOGA-ANN can be computationally intensive in the case of

large problems. In addition, premature convergence to a suboptimal solution may take place (Amin et al., 2012; Rocha and Neves, 1999). Additionally, the selection of appropriate parameters for both the ANN and the genetic algorithm is complex and can impact the overall performance of the model. Other drawbacks include that due to ANNs being black boxes, interpretability in the context of those models is reduced, the algorithm depends on the initial population, and its performance is sensitive (Montavon et al., 2018; Wimmer, 2018). Despite these challenges, MOGA-ANN remains a powerful tool for optimizing biomass briquette production (Ali et al., 2024), offering significant improvements in balancing quality parameters and advancing sustainable and low-carbon solutions in the field.

3.2.7. Machine learning for determination of emission characteristics

Studies on the use of machine learning for the prediction of gaseous emissions from the combustion of biomass, specifically biomass briquettes, are scarce in the literature. ANN was used to predict the major air contaminants emitted by biomass during the combustion process (Monteiro et al., 2024). The study used the ultimate properties of 166 biomass species from literature to train ANNs that can predict Carbon Monoxide, Carbon dioxide, Sulphur Oxides, and Nitrogen Oxides emitted during biomass combustion. The ANN models demonstrated excellent accuracy with MAPE between 0.001 and 12.4 %, MAE 0.001–5.8 Nm³ MAE, and RMSE 0.03–52.30 mg/Nm³. Another study used different numerical models including ANN to estimate the CO emissions from a biomass wood pallet combustion facility using boilers (Böhler et al., 2019). The ANNs provided a straightforward performance compared to other models like the Fuzzy and other mathematical models in the study. ANN was used to predict the ash yield and CO emission from the Co-combustion fruit bunch (EFB), palm kernel of shells (PKS), and kaolin (Oladosu et al., 2021). Results have indicated that with an increase in the combustion temperature and PKS fraction, ash yield and CO emission are generally reduced. The ANN proved strong predictive capabilities with R² values of 0.96 and 0.93 for ash yield and CO emission, respectively. These results provide evidence of the capabilities of ANN in emission prediction and the optimization of combustion processes. In comparison with other models, the deep neural network performed very well with the R² within the training processes between 0.8875 and 0.9992, and upon testing, it lay between 0.909 and 0.9991 (Kaleli et al., 2023). The application of machine learning models in predicting emissions resulting from biomass combustion has shown promising results. Further research is necessary to apply the models to this specific case of biomass briquettes. Research is also needed to determine how the different physical characteristics of biomass briquettes affect the emissions during combustion from different combustion setups. Model evaluation metrics are useful for testing these models' performances and selecting the most

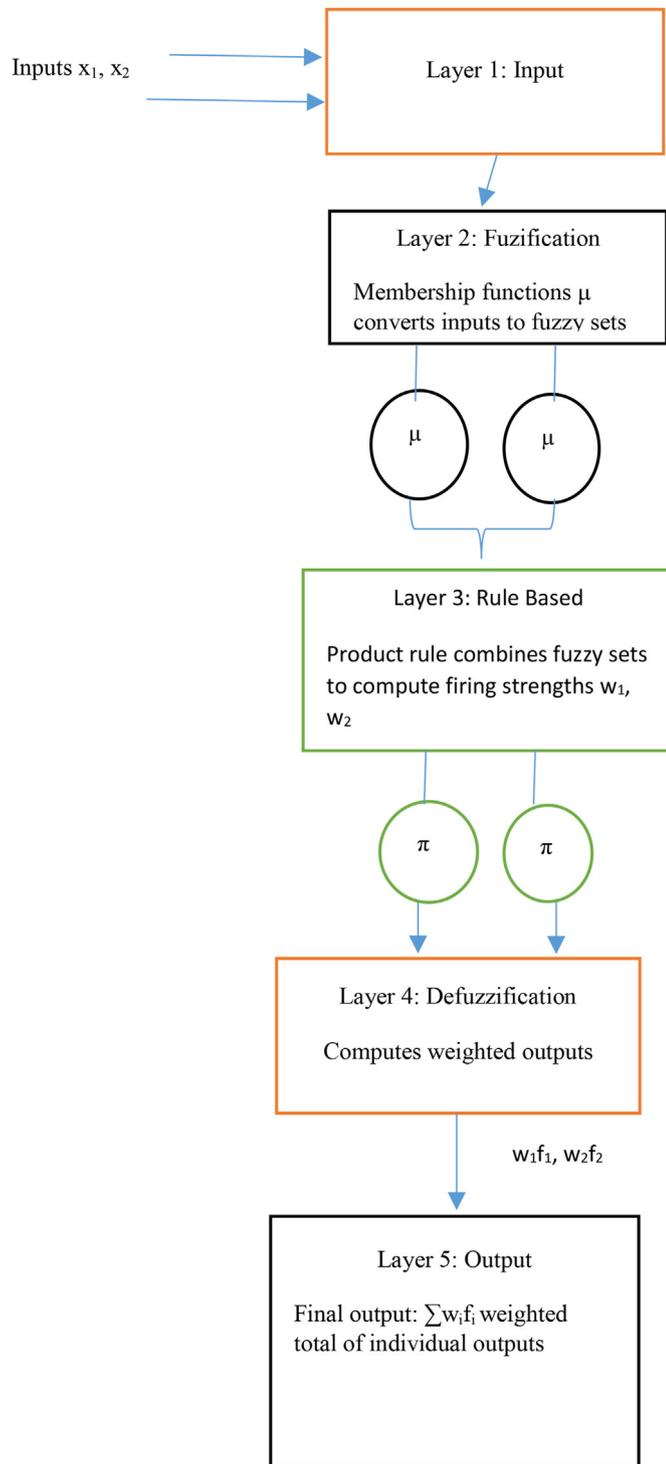


Fig. 6. Five-layer architecture of ANFIS, illustrating input, fuzzification, rule-based processing, defuzzification, and final output.

suitable models for different applications.

3.3. Model evaluation

The choice of evaluation metric for biomass briquette quality prediction depends on the nature of the data, the predictive task, and the desired outcomes. Several commonly used metrics include the Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and

Mean Absolute Deviation (MAD). Each of these metrics serves a distinct purpose and is suited to different modeling objectives as discussed here.

3.3.1. Evaluation metrics for regression problems

R^2 (Coefficient of Determination) measures the proportion of variance in the dependent variable that is explained by the model (Plevris et al., 2022). It is an important metric for assessing model fit but does not provide insight into the magnitude of errors. For instance, Extra Trees has an R^2 of 0.7595 (Kocer et al., 2023), meaning that the model explains about 76 % of the variance in the data. In contrast, CatBoost achieves an R^2 of 0.9921 (Kabas et al., 2024), indicating a much higher level of variance explanation (99.21 %). While R^2 is useful for understanding how well a model fits the data, it does not address the accuracy of individual predictions, which is why it is typically used alongside other metrics such as RMSE and MAE.

RMSE (Root Mean Squared Error) is useful when large errors are detrimental to the application (Plevris et al., 2022), such as when predicting properties like compressive strength in biomass briquettes. RMSE quantifies the average magnitude of errors, giving greater weight to larger errors. For example, Extra Trees has an RMSE value of 368.12 (Kocer et al., 2023), suggesting substantial prediction errors. In contrast, CatBoost has a much lower RMSE of 8.25 (Kabas et al., 2024), indicating a model with more accurate predictions. When large errors are particularly undesirable, as in compressive strength prediction, models with lower RMSE values are preferred.

MAE (Mean Absolute Error) provides a simple, interpretable measure of average error, treating all errors equally, regardless of their size (Plevris et al., 2022). It is more forgiving of larger errors compared to RMSE. For example, ANFIS reports an MAE of 0.2151 for training data (Bamisaye et al., 2024a) while CatBoost has an MAE of 6.10 (Kabas et al., 2024). MAE is particularly useful when the application can tolerate some level of error and is preferred when a simpler, more straightforward error measure is required. If biomass briquette properties like density or durability are being predicted, where slight deviations are more acceptable, MAE could be the most appropriate metric.

MAPE (Mean Absolute Percentage Error) is a valuable metric for comparing model accuracy across datasets with different scales. It provides a percentage-based evaluation, making it particularly useful for applications where comparisons are needed between models predicting properties with different units (Plevris et al., 2022). For instance, ANFIS has a MAPE of 1.1899 (Bamisaye et al., 2024a) for test data indicating that, on average, the model's predictions are off by 1.19 %. CatBoost, on the other hand, reports an extremely low MAPE of 0.0080654 (Kabas et al., 2024), reflecting its high accuracy. When comparing multiple models across different datasets, MAPE allows for a fair and consistent evaluation of prediction accuracy in percentage terms.

MAD (Mean Absolute Deviation) measures the variability in the predictions by calculating the average deviation of data points from the mean of the dataset. MAD helps assess how consistent a model is in handling data variability. For instance, MOGA-ANN has a MAD value of 35927.9648 (Ali et al., 2023), suggesting considerable spread in its predictions. In contrast, ANFIS has a MAD of 0.1902 for test data (Bamisaye et al., 2024a), indicating a model with less variability in its predictions. Although MAD is less commonly used in biomass briquette quality prediction, it can be an important metric when the dataset exhibits high dispersion or variability.

The selection of the most appropriate evaluation metric depends on the specific goals of the modeling effort, the characteristics of the dataset, and the significance of error types in the application. For critical properties like compressive strength or deformation energy, where large prediction errors can be particularly detrimental, models should prioritize minimizing large errors, making RMSE the preferred metric. On the other hand, for less sensitive properties like density or durability, where slight deviations from true values are more acceptable, MAE or MAPE may be more appropriate. When comparing models across datasets with different scales, MAPE offers a fair accuracy comparison in percentage

terms. Additionally, R^2 provides an overall assessment of model fit, but it should be interpreted alongside RMSE or MAE to fully capture both the model's explanatory power and error magnitudes. Finally, MAD can provide additional insights into the model's consistency, particularly when dataset dispersion or variability is a concern.

3.3.2. Model performance in biomass briquette prediction

In the analysis of machine learning models for biomass briquette quality prediction, several models exhibit varying degrees of effectiveness, as shown in Table 7. In the study by Kocer et al. (2023), Extra Trees outperformed the Random Forest, and Light Gradient Boosting with a low R^2 and MAPE of 0.7595 and 0.0799 respectively in the prediction of compressive strength of biomass briquettes as shown in Table 7. These metrics indicate a relatively good fit but suggest that there is still room for improvement in reducing prediction errors, especially in real-world applications where compressive strength is critical. Therefore, Kocer et al. (2023) recommended further optimizing Hyperparameters or using alternative models to enhance model performance. Similarly, CatBoost excelled in predicting deformation energy with the highest R^2 of 0.9921 and very low MAPE, RMSE, and MAE values, indicating superior predictive performance (Kabasi et al., 2024) underscoring its strong predictive power and minimal error margins.

ANFIS models demonstrate consistently strong performance with high R^2 values for both training and testing phases, showing minimal variability between the two, which indicates effective generalization and accurate predictions (Bamisaye et al., 2023; Bamisaye et al., 2024a). This suggests that ANFIS models are robust and able to generalize effectively to unseen data, which is crucial for real-world applications where new biomass sources may be used. ANN models similarly perform well in predicting different briquette properties, outperforming MLR models (Kumar et al., 2021). This is a reflection of the ability of ANN to handle data with nonlinear relationships as opposed to MLR. However, as noted in studies involving MOGA-ANN (Ali et al., 2023), such models can suffer from overfitting, where training performance significantly outperforms testing performance. This highlights the importance of using cross-validation and tracking both training and testing performance with RMSE and MAE to ensure generalization and robustness. Regularization techniques or cross-validation could help mitigate this in future endeavors.

3.3.3. Enhancing model generalizability in biomass briquette quality prediction

Enhancing the generalizability of predictive models is crucial for applying them to a wide range of biomass briquettes and processing conditions, thereby supporting scalable and sustainable solutions in biomass briquette production that advance low-carbon goals, while maintaining high predictive accuracy. This is particularly relevant as certain models, like MOGA-ANN (Ali et al., 2023), show promising results in training but reveal challenges in validation, reflecting the need for strategies that enhance their applicability across diverse scenarios.

Several strategies can be employed to improve model generalization. Cross-validation, particularly K-fold cross-validation, is commonly used for model validation in biomass briquetting studies (Kocer et al., 2023). This technique involves splitting the data into multiple folds, ensuring that each fold is used for both training and validation to provide a robust assessment of model performance. For example, a study on the prediction of the compressive strength of groundnut shells by Kocer et al. (2023) applied a 10-fold cross validation demonstrating the technique's ability to minimize overfitting and enhance model reliability. Despite these efforts, the authors recommended Hyperparameter optimization for further improvement, as models like Extra Trees still displayed low R^2 values (Kocer et al., 2023). Hyperparameter tuning also known as Hyperparameter Optimization involves adjusting of the model's Hyperparameters towards the optimal configuration. During the prediction of pallet stove performance (Kaleli et al., 2023), Hyperparameter optimization algorithms including Grid Search, Bayesian optimization, particle

swam and generic algorithm were used. The Optimized models gave good performance, showcasing the potential of such techniques in optimizing machine learning models for biomass feedstock. In addition, using a range of different kinds of biomass feedstock and processing conditions into the training data can help improve a model's robustness. For instance, while studies like Bamisaye et al. (2024b) and Kocer et al. (2023) focus on specific feedstock, expanding datasets to include multiple feedstock can further enhance model accuracy and adaptability in biomass briquetting. This approach ensures that the model is exposed to various scenarios and learns to generalize better across different types of biomass. By integrating these techniques, models can be refined to better handle diverse feedstock, promoting a circular economy through the sustainable use of various waste materials and reducing reliance on non-renewable resources. This approach not only optimizes production but also contributes to lower operational costs and decreased carbon emissions, aligning with broader sustainability goals.

3.3.4. Benefits of machine learning in the production of biomass briquettes

Machine learning models ensure significant benefits related to the production and combustion of biomass briquettes. ML models improve the accuracy of prediction of briquette quality parameters (Kocer et al., 2023; Kumar et al., 2021) improving overall quality control in conformity with briquette quality standards. This improvement in quality control contributes to broader sustainability goals by advancing resource efficiency, enhancing waste management practices, and promoting a circular economy.

Machine Learning models can improve combustive efficiency by accurately predicting the emissions from the combustion of biomass. For example, the application of the ANN successfully predicted key air pollutants based on the characteristics of the biomass (Monteiro et al., 2024). This helps in reducing emissions and increasing the efficiency of energy production. In summary, the optimization contributes to cleaner and greener energy practices as intended by the sustainable development goals.

These models have significant economic and operational advantages. Machine Learning models reduce the energy required for production through optimization of processing parameters (Kocer et al., 2023; Resende et al., 2022), leading to lower operational costs and minimized waste. Better forecasting of properties and combustion emissions of biomass further assists the transition to low- and zero-carbon technologies due to reduced negative environmental impacts.

3.3.5. Computational resources

However, the computational efficiency of machine learning (ML) models is crucial for their use in biomass briquette production. Simple models, like Random Forest, Extra trees and Light Gradient Boosting (Kocer et al., 2023), offer practical solutions for small-scale producers with limited resources with constrained computational resources. In contrast, more complex models like ANN (Bamisaye et al., 2023) and CNN (Saptadi et al., 2023b) provide higher accuracy but are computationally intensive and can make it harder for users to understand the predictions. Balancing computational requirements and interpretability is essential. Depending on the scale and resources of the production environment, simpler models may suffice, but for large-scale, high-accuracy requirements, ANN and CNN models are highly beneficial. This balance enables scalable and sustainable green briquette production while encouraging industry adoption.

4. Gaps in the current literature

However, most of the current research on the use of machine learning for biomass briquettes does not cover a wide range of materials used in briquette production (Bamisaye et al., 2024a; Kumar et al., 2021; Resende et al., 2022), and therefore, expansion of research to a broader range feedstock would improve the generalization of ML models. Current Research focuses more on the prediction of the physical properties of the

biomass briquettes and the calorific value leaving out combustion characteristics such as burning time, burn rate, ignition time, and associated emissions. Additionally, the limited availability of datasets encompassing diverse feedstock properties, binder types and ratios, production parameters, and comprehensive physical and combustion characteristics, further impacts the ability of models to predict performance across different scenarios accurately. Integration of such parameters within the ML models will provide comprehensive information on briquette behavior during combustion and the environmental impact. Expanding ML studies to incorporate these factors, alongside a broader range of feedstock, will offer a more comprehensive understanding of biomass briquette's behavior and environmental impact. This will support the development of sustainable and efficient industrial practices toward developing reduced carbon footprints with improved green energy solutions.

5. Implications for stakeholders

Researchers play a crucial role in advancing the application of machine learning (ML) in biomass briquette production. There are several opportunities for research contributions in this area. First, researchers can focus on developing and refining ML models to improve the accuracy and reliability of predictions for key briquette quality parameters such as density, moisture content, and combustion characteristics. This involves exploring diverse ML algorithms and optimizing them for different feedstock types and production conditions. Additionally, researchers can contribute to the creation of comprehensive and standardized datasets that encompass a wide range of biomass materials and production processes, addressing current data gaps. By conducting interdisciplinary studies that integrate ML with material science, environmental science, and engineering, researchers can drive innovation and enhance the effectiveness of biomass briquette production.

For industry professionals, integrating ML into biomass briquette production presents significant opportunities for improving efficiency and product quality. ML models can provide valuable insights for optimizing the formulation and production processes, resulting in briquettes with enhanced physical and combustion properties. Industry professionals can leverage ML tools to monitor and control production parameters in real-time, leading to better consistency and reduced waste. Implementing ML-driven predictive maintenance can also minimize downtime and operational costs. Furthermore, ML can aid in the development of customized briquette formulations tailored to specific applications or environmental conditions. By adopting these advanced technologies, industry professionals can achieve higher efficiency, quality, and sustainability in biomass briquette production.

Policymakers play a vital role in fostering the integration of ML into green energy technologies, including biomass briquette production. To support this transition, several policy recommendations can be considered. First, policies should encourage research and development in ML applications for biomass and other green technologies, including funding for innovative projects and collaborations between academia and industry. Providing incentives for the adoption of ML technologies in the biomass sector can also drive industry uptake and accelerate the transition to more efficient and sustainable production methods. Additionally, establishing standards and guidelines for data collection and model validation can help ensure the reliability and comparability of ML applications. Finally, promoting educational programs and training for industry professionals on ML technologies can enhance their ability to effectively implement and utilize these tools. By creating a supportive policy environment, policymakers can facilitate the advancement and widespread adoption of ML in green energy technologies.

6. Conclusion

This review highlights the transformative potential of machine learning (ML) in enhancing the quality and sustainability of biomass

briquette production. ML models have proven invaluable in predicting key briquette properties such as density, moisture content, particle size, and combustion characteristics. These advances enable precise control over briquette formulation and production, leading to better performance, higher efficiency, and a significant reduction in environmental impact. The integration of ML in biomass briquette production supports the creation of higher-quality products that meet stringent industry standards, contributing to the development of more sustainable energy solutions.

Looking forward, there is vast potential for ML to further advance the field, particularly by integrating additional critical combustion parameters such as calorific value, ignition time, burning rate, and emissions into predictive models. These parameters are key to understanding and optimizing the performance of biomass briquettes during combustion. By leveraging ML algorithms, it is possible to predict the ignition time and burning rate, which are crucial for ensuring the efficient and reliable use of biomass briquettes. Such predictions would enable producers to design briquettes that ignite quickly, burn more consistently, and release energy efficiently, ultimately improving fuel utilization and reducing energy consumption.

Equally important is the role of ML in emission prediction and reduction. Harmful emissions, such as carbon monoxide (CO), nitrogen oxides (NOx), and particulate matter (PM), are significant concerns during the combustion of biomass. Machine learning can help predict and optimize the emission profiles of biomass briquettes, enabling manufacturers to produce briquettes that minimize harmful pollutants without compromising on combustion efficiency. By incorporating emission data into ML models, it becomes possible to design briquettes that contribute to cleaner air and a more sustainable energy ecosystem.

The future of ML in biomass briquette production lies in further research to fill existing gaps, such as the development of comprehensive datasets that include various feedstocks, binder types, and combustion conditions. Additionally, real-time data monitoring during the combustion process, coupled with adaptive ML models, could provide ongoing optimization, ensuring that the combustion of biomass briquettes remains both efficient and environmentally friendly.

To achieve these advancements, collaboration between researchers, industry professionals, and policymakers will be essential. By fostering cross-sector partnerships and promoting knowledge exchange, the field can accelerate the adoption of ML technologies, ensuring practical, scalable solutions for biomass briquette production. This interdisciplinary approach will be crucial in overcoming challenges related to data access, computational resources, and regulatory compliance.

In conclusion, the continued integration of machine learning in biomass briquette production promises to revolutionize the industry. By focusing on combustion parameters such as ignition time, burning rate, and emissions, ML models can help produce high-performance, low-emission briquettes that support sustainable energy systems. The combined efforts of researchers, industry stakeholders, and policymakers will be key to unlocking the full potential of ML in creating cleaner, more efficient biomass energy solutions for the future.

CRediT authorship contribution statement

Constance Nakato Nakimuli: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation. **Fred Kaggwa:** Writing – review & editing. **Johan De Greef:** Writing – review & editing. **David Kilama Okot:** Writing – review & editing, Writing – original draft, Supervision. **Julien Blondeau:** Writing – review & editing, Supervision, Resources, Funding acquisition. **Simon Kawuma:** Writing – review & editing, Supervision.

Declaration of generative AI in the writing process

During the preparation of this work, the authors used ChatGPT to improve readability and language. After using this tool, the authors

reviewed and edited the content as needed and take full responsibility for the content of the publication.

Funding information

This research has been funded by the University as a Facilitator Community Based Sustainable Solutions to Demographic Challenges in South Western Uganda (UCoBS) project which is a collaboration between Mbarara University of Science and Technology (MUST) Uganda, Vrije Universiteit Brussel (VUB) Belgium, supported by the VLIR-UOS Institutional University Cooperation (IUC) program.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Constance Nakato Nakimuli reports financial support was provided by MUST UCObS. Constance Nakato Nakimuli reports financial support was provided by Flemish Inter-university Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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