Chapter

Biochar and Application of Machine Learning: A Review

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Abstract

This study discusses biochar and machine learning application. Concept of biochar, machine learning and different machine learning algorithms used for predicting adsorption onto biochar were examined. Pyrolysis is used to produce biochar from organic materials. Agricultural wastes are burnt in regulated conditions to produce charcoal-like biochar using pyrolysis. Biochar plays a major role in removing heavy metals. Biochar is eco-friendly, inexpensive and effective. Increasing interest in biochar is due to stable carbon skeleton because of ease of sourcing the precursor feedstock and peculiar physicochemical. However, artificial intelligence is a process of training computers to mimic and perform duties human. Artificial intelligence aims to enable computers to solve human challenges and task like humans. A branch of artificial intelligence that teaches machine to perform and predict task using previous data is known as machine learning. It uses parameters called algorithms that convert previous data (input) to forecast new solution. Algorithms that have been used in biochar applications are examined. It was discovered that neural networks, eXtreme Gradient Boosting algorithm and random forest for constructing and evaluating the predictive models of adsorption onto biochar have all been used for biochar application. Machine learning prevents waste, reduces time and reduces cost. It also permits an interdisciplinary means of removing heavy metals.

Keywords: review, machine learning, biochar, AI, adsorption

1. Introduction

The world is embracing the fourth industrial revolution and adapting technology in every sphere of human endeavours. 4IR is adjusting ways humans engage, work and live [1]. Its ushers humanity into a new phase caused by incredible technological advancements comparable to the first, second and third industrial revolutions. Machine learning has been deployed simply in different aspects of human lives to living and cost [2, 3]. It is gaining interest in biochar. Biochar is a produced using pyrolysis. Forestry and agricultural wastes are burnt in regulated conditions to produce biochar [2, 3]. This study examines the various algorithms used in machine learning to predict adsorption in biochar.

Fourth Industrial Revolution will alter patterns of key sectors. This includes technological shift, deviation in societal patterns and processes caused by increased interconnection among other features [4]. It hopes to transform the ways things are done. Things will communicate via networks, data sharing and the likes. It is an era that will see machines perform tasks more than before. The machines will learn using previously generated data and transform those learning to solve human challenges. This is all-encompassing, including in biochar.

Biomass conversion without oxygen produces a solid product (biochar) [5–7]. Stability of biochar is responsible for carbon sequestration [8]. It could be a way to combat climate change [9, 10]. Biochar improves soil fertility. It increases agricultural yield in acidic soils [11, 12]. Biochar is made from various organic waste feedstocks, including agricultural waste and sewage sludge [13, 14]. Biochar has many applications, including heat and power generation and a soil amendment. Process parameters and feedstock influence the characteristics of carbonised biomass. Selection of acceptable conditions to manufacture a char with the necessary qualities thus necessitates quantitative and qualitative knowledge of interdependence and affecting factors [15].

In machine learning, input is a set of instructions (algorithms) used to generate result. It learns from previous data to perform and optimise operations. Attempts have been made to adapt machine learning in biochar [16, 17].

There have been attempts to implement machine learning in various aspects of biochar [18], review machine learning [19, 20] and review biochar [21]. However, there is limited literature focusing on the review of machine learning in biochar. This forms the basis of this study. The concept of biochar is examined and, after that, machine learning. This is closely followed by examining biochar and machine learning.

2. Biochar: history, properties and applications

2.1 History of biochar

The term 'biochar' is a late-twentieth-century English neologism. It is from a Greek words 'o, bios' or 'life' and 'char' or 'clarification' (charcoal produced by carbonisation of biomass) [22]. It is charcoal, prevalent in soil, aquatic ecosystems and animal digestive systems and participates in biological processes. Biochar usage for soil nutrient retention and improvement started in the Brazilian Amazon about 2000 years ago [23]. John Miedema, a commercial fisherman, organic farmer and inventor, first learned about biochar 5 years ago while looking for a better solution to clean up effluent from a dairy manure digester [24]. Biochar was made by pre-Columbian Amazonians by covering burning biomass with soil in ditches [25]. Terra preta de Indio was the name given to it by European settlers [26].

2.2 Production of biochar

Biochar is made by heating biomass without oxygen, either completely or partially [27, 28]. The most common process for making biochar is pyrolysis, which can also be found in the early stages of gasification ad combustion [29]. Biochar is made from different biomass sources, including solid wastes, plant materials, biomass from wood, agricultural residues and so on [30, 31]. Pyrolysis is a typical technique to produce biochar. The process is performed between 400 and 1000°C [32, 33]. Pyrolysis, hydrothermal carbonisation, gasification, flascarbonisation and torrefaction are some of the most prevalent thermochemical processes used to make biochar [34–36]. Pyrolysis is the most common biochar production method of all of these [37]. The process is depicted in Eq. (1).

$$C_6H_{8.7}O_4 \rightarrow C_3H_{1.4}O_{0.4} \tag{1}$$

$$\text{Biomass} \rightarrow \text{Biochar}$$

Biochar is created the same way as charcoal, but it is meant to be used as an adsorbent and a soil amendment [38]. The end use of the material is, in essence, the key. If it is meant to be used as a fuel, it is called charcoal, and it is made with the best fuel qualities possible.

2.3 Properties of biochar

Biochar's efficacy as a soil amendment is influenced by its chemical and physical qualities. As biochar interacts with bacteria, mineral substances and soil organic and plant roots, its characteristics alter. The biochar qualities affect its performance as a soil amendment.

Biochar comes in various forms, each with its own set of characteristics. Biochar's qualities impact how well it works as a soil amendment [39]. It can be altered by conditioning, which includes adding minerals, nutrients and/or microorganisms to the biochar after it has been made [40]. Biochar from clean biomass differs from biochar produced with field residue in terms of the qualities. This is because the field residue biochar has been mixed with fertilisers, soil and manure. The characteristics of biochar are altered when it is mixed with soil organic, mineral substances and bacteria. Biochar improves with age.

Biochar properties are influenced by the type of biomass used [41]. As long as the biomass is not polluted with hazardous compounds, it can be used to make biochar (e.g. heavy metals, PCBs). Biochar feedstocks include plant residues, grasses, industrial wastes, woods, seaweed, manures, MSW, food waste [42]. **Figure 1a** shows the pyrolysis of seaweed to produce a biochar. **Figure 1b** shows the evolution of biochar from biomass.

The properties of biochar are grouped under chemical and physical [45] in **Table 1**.

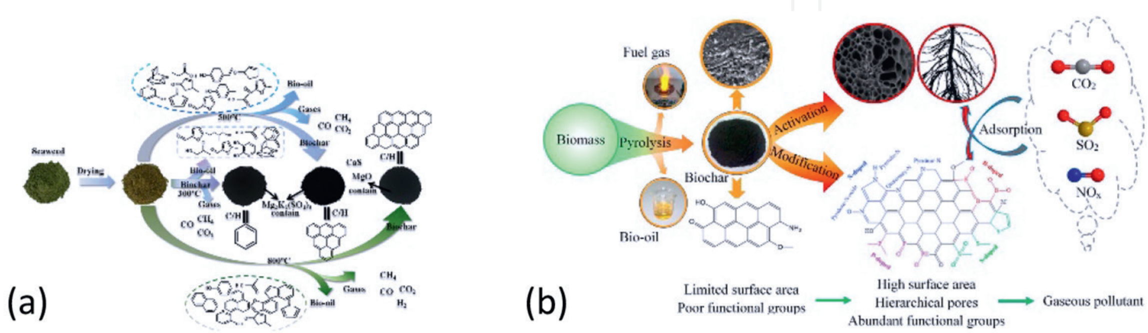

Figure 1.
(a) Process of seaweed pyrolysis to biochar [43] and (b) biomass to biochar [44].

Properties	Parameters
Physical	Particle size, bulk density, hydrophobicity, water holding capacity, macro and micro-porosity, particle density and grindability
Chemical	Electrical conductivity, micro and macro-nutrient content, toxic compounds, soluble organic compounds, cation and anion exchange capacity, heavy metals, proton activity and liming value

Table 1.
Summary of biochar properties.

2.3.1 Physical properties of biochar

Biochar's physical features influence its environmental mobility, interactions with minerals, soil water, nutrients and usefulness as an ecological niche for soil microorganisms and mycorrhizal fungus by soil microorganisms mycorrhizal fungus providing surfaces, growing space and predator protection [46]. Physical parameters such as particle density and size, porosity, bulk density and surface area are numerical and action connected. Porosity affects particle density and surface area [47]. Biochar with high porosity and low density may hold more water. However, wind and water easily remove such biochar. The quality of biochar is affected by heating rate, biomass type [48] as enumerated in **Figure 2**.

Grass biochar has a particle density of 0.25–0.3 g/cm^3, while wood biochar has 0.47–0.6 g/cm^3 [49]. Particle density of biochar affects the loss and movement in water or wind [50]. Biochar with a low bulk density can be used to remediate wall gardens and compacted soils. Pore sizes can vary by six orders of magnitude and are classed as macro-, meso- and micro-pores, with varied implications for biochar interactions with the environment [51, 52]. Most woody biochar has low bulk densities, medium-to-high surface area and porosity [53, 54]. The process utilised to make biochar has an impact on porosity.

Hydrophobicity impacts biochar's water uptake, its water holding capacity and microbial interactions. Tars (aliphatic chemicals) condensing on the charcoal surface during pyrolysis induce hydrophobicity. Biochar has high hydrophobic at low temperatures. However, longer pyrolysis times can lessen hydrophobicity. Hydrophobicity may diminish as biochar mixes with soil.

A low Hardgrove Grindability Index (HGI) indicates that the material is difficult to grind, whereas a high HGI value suggests that the material is easy to grind [55, 56]. HGI of 80–120 can be achieved for woody biochar having volatile matter content of about 20%, which is commonly achieved at temperatures around 600°C, defining charcoal as easily grindable.

2.3.2 Chemical properties of biochar

Persistent carbon is composed of carbon ring structures, with some nitrogen and oxygen thrown in. Structures' ring sizes are determined by temperature of biochar production. Biochars' water-soluble and mineralisable chemicals can nourish bacteria and can boost seeds and plant nutrient and yield. Water-extractable organics are substantially more abundant in low-temperature biochars. Total and bioavailable polycyclic aromatic hydrocarbons (PAH) have maximum acceptable limits. A common (90%) PAH in biochar is naphthalene. Many biochars at 350–500°C have included mineralisable organic molecules that benefit plants and soil [57, 58]. Low dosages of

Figure 2.
Factors affecting biochar quality.

phenols, butenolide (a component of tobacco), carboxylic and fatty acids and even PAH can encourage plant development. In contrast, high quantities can inhibit or kill it, a phenomenon known as hormesis.

2.4 Merit and demerit of biochar

Biochar continues to attract interest owing to its vast potential and benefit. However, there are some disadvantages associated with it. Discussed below are the merit and demerit of biochar.

2.4.1 Merit of biochar

Biochar is a carbon-rich substance, some scientists believe that it is the secret to soil renewal [59]. Biochar, which is relatively light and porous, can act as a sponge and provide a home for various beneficial soil microbes useful for soil and plant health. It increases agricultural production. Biochar can remove CO_2 from the atmosphere for long periods and provide other environmental benefits [60]. Plants transform carbon dioxide from the air into organic material, or biomass, through photosynthesis. It helps in climate change mitigation [10].

2.4.2 Demerit of biochar

It absorbs nutrients, resulting in a nutrient deficit in growing plants [47, 61]. Biochar application regularly creates soil compaction, which reduces crop yield. Land loss is also due to erosion, pollution risk, agricultural residue removal and worm life rate reduction.

2.5 Application of biochar

Biochar is useful in several applications [62]. It is used to enhance soil health via soil amendment. It also serves as microbial carrier immobilising agents for remediation of toxic metal and organic contaminant in water and soil. It is catalyst for industrial application, porous materials for mitigating greenhouse gas emission and odorous compound. It is used as feed supplements to improve nutrient intake efficiency, animal health and hence productivity [63]. **Figure 3** shows the influence of biochar properties on the agriculture and soil conditions.

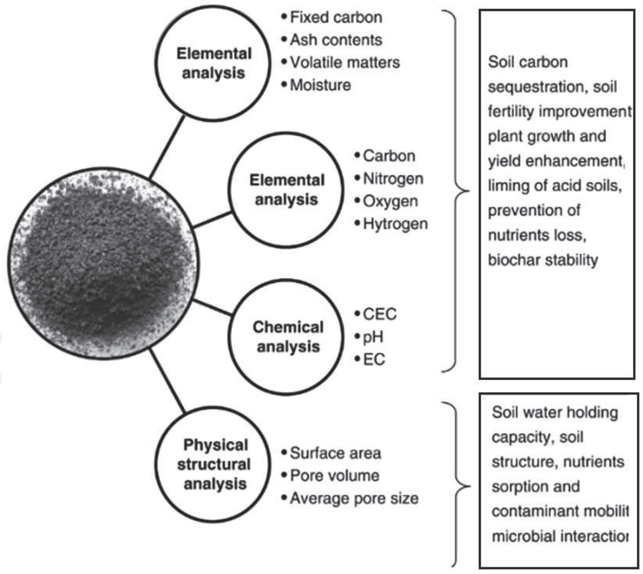

Figure 3.
Impact of biochar properties on soil conditions and agriculture [48].

2.5.1 Biochar for soil amendment

Biochar has a lot of potential as a long-term product for improving agricultural soil health and fertility. The manufacture of biochar and its impact on soils can help to reduce the need for commercial fertilisers. Diverse research has also reported that addition of biochar to agricultural soil can aid in reducing greenhouse gas emission [64–67].

Biochar is utilised as an agricultural soil amendment because it has a lot of fascinating properties, such as high carbon content, a high pH, high stability, a high porosity and a high surface area [68, 69]. Over the last few years, multiple research studies have been conducted to analyse the global impact of biochar on diverse agricultural soils [70, 71]. Biochar has improved soil's chemical, physical and biological qualities, enhancing crop productivity [72, 73]. Furthermore, biochars with a high surface can be utilised as soil remediation technique to adsorb both inorganic and organic contaminants, for instance, heavy metals, and pesticides, hence minimising leaching into waterway. Once applied to carbon in biochar, soils, that are highly stable, can be sequestered for more than 1000 years.

2.5.1.1 Application of biochar for soil amendment

When utilised as soil amendments, biochar is incorporated into the plant's root zone – the area of soil surrounding a plant's roots – ideally into 4–6 inches of soil depth. Increasing the time nutrients stay in the soil by mixing up to one part compost with one part biochar, most gardeners start with a ratio of 10 parts compost to one part biochar to ensure that plants tolerate it well.

Several materials such as green waste [74], rice straw [75], poultry litter [76] and other materials have been used for producing biochar using vacuum pyrolysed and other methods of biochar for soil amendments [77].

2.5.2 Carbon sink

A carbon sink is any natural or artificial reservoir that indefinitely gathers and stores carbon-containing chemical compounds [78]. Also, anything that absorbs more carbon from the atmosphere than it releases, such as plants, the ocean and soil, is a carbon sink. Oceans are the primary natural carbon sinks, absorbing over half of all carbon released [79]. Carbon dioxide is sucked from the atmosphere by plants for use in photosynthesis. On the other hand, a carbon source is anything that releases more carbon into the atmosphere than it absorbs, such as fossil fuel combustion or volcanic eruptions [80]. Carbon is deposited on our planet in four major sinks: (1) organic molecules in living and dead organisms in the biosphere; (2) carbon dioxide in the atmosphere; (3) organic matter in soils; and (4) fossil fuels and sedimentary rock deposits such as limestone and dolomite in the lithosphere. Because the process takes a supposedly carbon-neutral phase of naturally decaying, biochar reduces CO_2 in the environment.

Growing plants or collecting waste biomass, converting it to biochar and adding it to soils remove carbon dioxide (CO_2) from the environment: plants growth eliminates CO_2 from the atmosphere and produces additional biomass; the carbon in that biomass is transformed into a stable form [81, 82]. Biochar production can offset about 12% of world's greenhouse gas emissions. At \$30–120 per ton of CO_2, biochar might sequester 0.5–2 $GtCO_2$ per year by 2050 [83, 84]. According to the scholarly literature, sequestration rates range from 1 to 35 $GtCO_2$ each year, with a potential of 78–477 $GtCO_2$ in this century [85, 86].

2.5.3 Biochar for water retention

Water retention refers to how much water a soil can keep for its crops, allowing plants to have more water available. Biochar can improve the soil's water retention and holding ability due to its porous structure. An agriculturally applicable biochar amendment of 5% biochar (approximately 100 metric tons/ha) leads to a 24% increase in water retention capacity over unamended soil or a 50% increase [87]. Researchers have understudied the impact of biochar on water retention [88], on sandy soil [89], clay [90], the application in different agricultural soil [91] and the relationship between plant and water [92]. There has also been the study of southeastern coastal soil [93] and midwestern agricultural soil [94].

2.5.4 Biochar for stock fodder

Stock fodder, also known as provender, is an agricultural feed used to feed domesticated animals such as cattle, rabbits, sheep and horses [95]. Fodder crops are divided into two categories: temporary and permanent. Fodder is used to describe the crops gathered and utilised for stall feeding. Forage is a vegetative matter used as animal feed, whether fresh or stored. Grasses, legumes, crucifers and other forage crops are farmed and utilised as hay, grazing, fodder and silage.

Xie et al.[96] provided a thorough investigation of biochar's technical features and possible applications as an engineered material for environmental remediation. Mandal et al. [97] presented quantitative data and discussed the benefits of biochar composites over pure biochar. The synthesis of nano-metal-aided biochar and its features and applications in soil improvement and heavy metal removal are discussed. Shakoor et al. [98] discuss how to boost biochar's heavy metal sorption capability by activating it with steam or acids/bases and impregnating biochar-based composite with mineral, organic compound and carbon-rich material. Biochars' chemical/physical activation of biochar can improve their surface area, resulting in better functionality, while pretreatment/modification techniques aid in developing new sorbent with efficient surface attribute for heavy metal removal from aqueous solution using biochar as a supporting media. This is essential because heavy metal sorption is driven by type of biochar, heavy metal species and various processes, including physical binding, complexation, ion exchange, surface precipitation and electrostatic interactions. Efforts were also made to review the application of biochar to remove heavy metals and toxic elements in water and wastewater [99, 100].

2.6 Future outlook of biochar

Wood-based biochar is the most popular product, accounting for approximately 64% of the market. Soil conditioner is the most popular application, accounting for almost 82% of the market.

The global biochar market is expected to be worth USD 314.6 million in 2022, with a readjusted size of USD 524.7 million by 2028, representing an 8.9% CAGR (compound annual growth rate) over the research period. From 2021 to 2030, the global biochar markets are expected to increase at a CAGR of 13.2%, from $170.9 million in 2020 to $587.7 million in 2030. Carbon Gold, The Biochar Company (TBC), Biochar Supreme, Cool Planet, Black Carbon and Swiss Biochar GmbH, among others, are global biochar significant players. The top three firms account for roughly 20% of the market [101].

3. Machine learning: history, algorithm and application

Machine learning (ML) is a process of predicting values using a previous learning. It is a subset of AI. It uses set of instructions called algorithm. ML uses algorithm to emulate variable or humanity. AI is used to solve complex tasks like how humans solve problems. There are four types of algorithms. They are reinforcement, unsupervised, semi-supervised and supervised. Python, Java, C++, R and JavaScript are among the top five programming languages and libraries for machine learning. Python is the language of choice for machine learning engineers, with more than 60% of them adopting and prioritising it for development since it is simple to learn. A little coding knowledge is required for the effective deployment of machine learning.

3.1 History of machine learning

An American IBMer (Arthur Samuel) was first to use machine learning in 1959 [102, 103]. Another term used is 'self-teaching computer' [104, 105]. A book on machine learning for pattern categorisation by Nilsson dominated the1960s [106]. Pattern recognition continued till the 1970s [107]. An approach for teaching neural network using 40 character recognition by computer terminal was documented in 1981 [108, 109]. This terminal included 4 special symbols, 26 letters and 10 digits. Tom Mitchell opined 'A computer program is said to learn from experience E for some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E'. This became accepted machine learning definition [110, 111]. However, the definition provided operational description of the ML tasks instead of cognitive. It aligns with Alan Turing's method 'Computing Machinery and Intelligence', replacing 'Can machine think' with 'Can machines do what we (as thinking creatures) can achieve' [112].

The goal of modern ML is to classify data using standard models and generate predictions about future outcomes using these models. A stock trading machine learning system may provide the trader with future prospective predictions [113, 114].

3.2 Theory of machine learning

Most beginners' main goal is to generalise what they have learned [115]. Generalisation is ML ability to execute precisely, previously unseen data using algorithm. Data (training) originate from new probability distribution. It represents space of occurrences. Optimisation prediction requires general model development. Computational learning theory is analysis of performance of algorithms. Training sets are limited because of future uncertainty. Learning theory rarely provides guarantees about algorithm performance. Probabilistic performance bounds are tremendously widespread. Bias-variance decomposition is used for generalisation error.

For the best generalisation outcomes, the hypothesis' complexity needs reflect the intricacy of the functions behind the data. If the assumption is fewer intricate than the functions, the system will under-fit the data. Increment in the complexity of the model reduces training error. Poor generalisation due to overfitting is caused by complicated hypothesis of model [116]. Learning theorists look at the temporal intricacy and feasibility of learning in addition to performance bounds. A computation is deemed viable in computational learning theory if it can be completed in polynomial time [117].

3.3 Classification of machine learning approach

ML is classified as reinforcement, unsupervised and supervised based on feedback or signal as depicted in **Figure 4** [118, 119].

Optimisation problem is solved using reinforced and unsupervised learning [118–120]. Although, supervised learning uses trained labelled data to produce result [121, 122]. Unsupervised learning uses unguided structure to solve problem [123]. Unsupervised learning is either intended or a means to an end (finding hidden patterns in data) (feature learning). It is used to obtain hidden pattern or future learning. Reinforcement learning is the third type. It is interaction in a dynamic circumstance. An example is driving on the road on the computer. Another example is engaging an opponent in competitive game [124]. Incentives (data) are fed to the software to help solve problem.

Unsupervised learning exposes latent patterns and structures from unlabelled data. Supervised learning solves problem using guided learning [125]. **Figure 5** depicts the most often used supervised algorithms.

Deep learning is used to clean heavy metal by constructing improved adsorption models. Machine learning or deep learning can develop models depending on data complexity, dimensionality and end use [127]. However, challenges of complexity and dimensionality are improved by deep learning with encoder.

3.4 Models of machine learning

Machine learning entails building a model that has been guided by training data. It can subsequently process more data to produce prediction. For machine learning systems, different models have been utilised and investigated. These are shown in **Figure 6**. The models include artificial neural networks, decision trees,

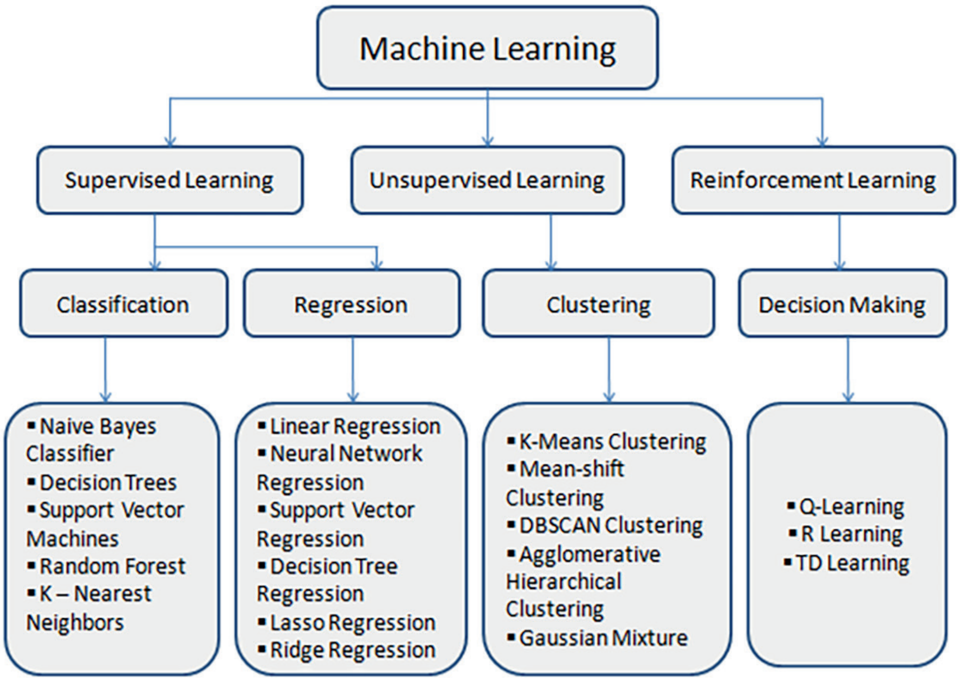

Figure 4.
Classification of machine learning.

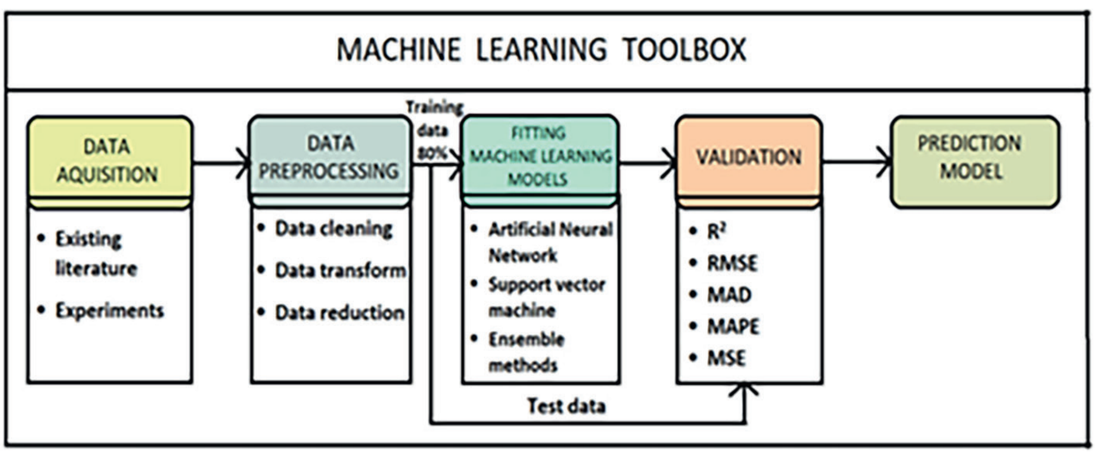

Figure 5.
Flowchart of supervised machine learning procedure [126].

support-vector machines, regression analysis, genetic algorithms, Bayesian networks, training models and federated learning [129–131].

The following models have been used in biochar applications. An overview is given for understanding the models.

i. Artificial Neural Networks (ANN) have become increasingly popular [132, 133]. ANN mimics the human brain with parallel processing to develop complex relationship between independent and dependent variables by developing structures for the model training via experimental data and the tool forming pattern between output and input data. It is a great tool because of its benefits in non-linear system adaptations and approximation without knowing the variables' relationship and ease of use [134].

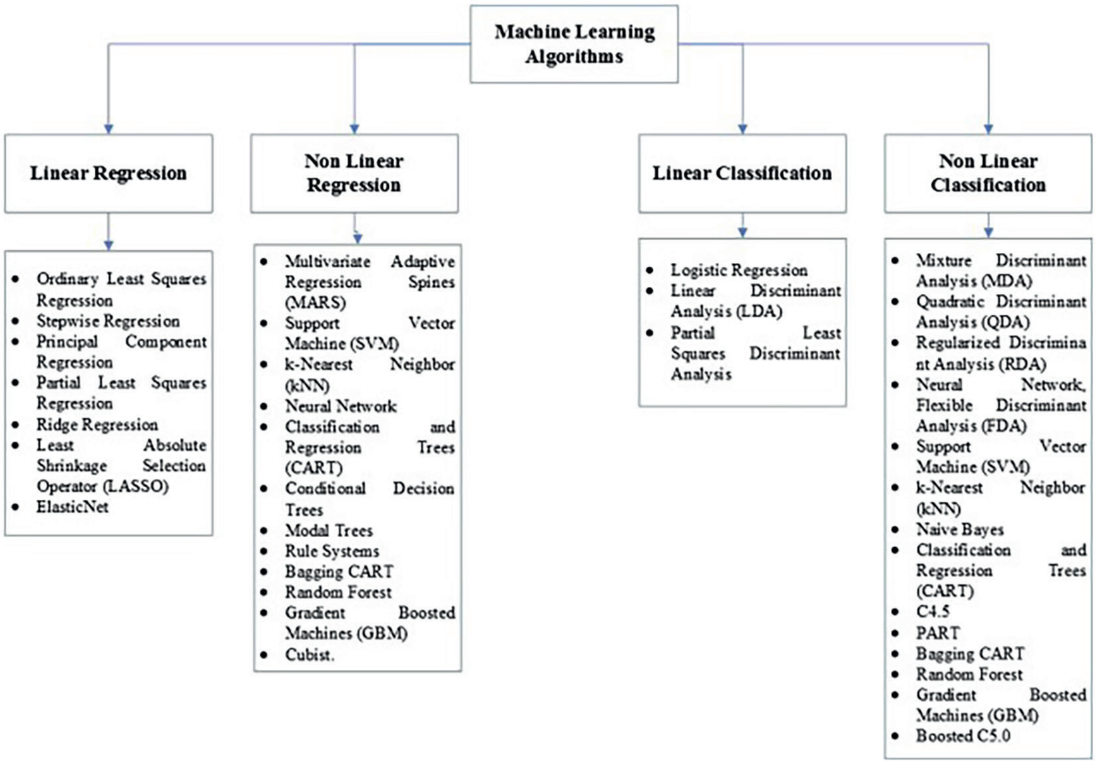

Figure 6.
Algorithms of machine learning [128].

ii. Random forest (RF) models are machine learning models that use the results of a series of regression decision trees to predict the output. Each tree is built independently and is based on a random vector sampled from the input data, with the same distribution across the forest. Using bootstrap aggregation and random feature selection, the predictions from the forests are averaged [135]. RF models are reliable predictors for small sample numbers and high-dimensional data. The RF classifier is an ensemble approach for training several decision trees parallel with bootstrapping and aggregation, often known as bagging [136].

iii. Support-vector machine

A support-vector machine (SVM) is a supervised machine learning model that uses classification techniques [137]. SVM models can categorise new text after being given sets of labelled training data for each category. Though we might also argue regression difficulties, categorisation is the best fit. The SVM algorithm aims to find the optimum line or decision boundary for categorising n-dimensional space into classes so that additional data points can be readily placed in the correct category in the future [138, 139]. A hyperplane is a name for the optimal choice boundary. The goal of the SVM algorithm is to find a hyperplane in an N-dimensional space that categorises data points. In SVM, a kernel is a function that aids in problem-solving. They give shortcuts to help avoid doing complicated mathematics. The amazing thing about kernel is that it allows us to go to higher dimensions and execute smooth calculations. Kernels allow us to go up to an infinite number of dimensions. SVM is used for regression and classification of problems. It is a linear model. It can solve both linear and nonlinear problems and is useful for a wide range of applications.

C is a hypermeter that is set before the training model to control error, and Gamma is another hypermeter that is placed before the training model to give the decision boundary curvature weight.

iv. eXtreme Gradient Boosting Model

Gradient boosting is a machine learning technique used for various applications, including regression and classification [140, 141]. Extreme Gradient Boosting (XGBoost) is an open-source package that implements the gradient boosting technique efficiently and effectively. Extreme Gradient Boosting is a tree-based method that belongs to Machine Learning's supervised branch. It's a machine-learning algorithm that can predict classification or regression. It returns a prediction model in the form of an ensemble of weak prediction models, most commonly decision trees [142].

3.5 Applications of machine learning

The following are some machine learning applications. Image and speech recognition, traffic prediction, self-driving cars, product recommendation, online fraud detection, stock market trading, medical diagnosis, automatic language translation, email spam and malware filtering, Alexa, Google assistant and Google Maps [119].

3.5.1 Image recognition

Image recognition is one of the most common machine learning applications [143]. It's utilised in identifying things such as people, places and digital photograph. Automatic buddy tag suggestion is a commonly used facial identification and picture recognition. Facebook has tools that suggest friends auto-tagging. When we submit photos with our friends Facebook, we obtain automatic tags recommended with their names powered by machine learning's face identification and algorithm recognition. It is based on the 'Deep Facia' Facebook projects that manage face recognition and individual identification in photos.

3.5.2 Speech recognition

The user of Google has the option to 'Search by voice', which falls under recognition of speech and is a prominent machine learning application. Recognition of speech, frequently referred to as 'Computer speech recognition' or 'Speech to text', is the turning process of voice instruction to text. Machine learning technique is now used widely in speech recognition application [144]. Technology of speech recognition is utilised by Alexa, Google Assistant, Siri, and Cortana to obey voice command.

3.5.3 Google Maps is used when visiting a new location or using an app hailing taxi

The map provides the best route with the shortest routes and forecasts traffic condition. It utilises two techniques in anticipating traffic condition, such as whether traffic is clear, extremely congested or sluggish moving: The vehicle's location is tracked in real time via the Google Map app and sensor. At the same time, the average time has been taken on previous days. Everyone making use of Google Maps contributes to the improvement of the apps. It collects data from the users and transmits it back to the database to improve its performance.

3.5.4 Product suggestions

Different entertainment and e-commerce organisations, for instance, Netflix, Amazon and others use machine learning to make products recommendation to user. We begin to receive advertisements for the same goods while browsing the internet on the same browser, because of machine learning, whenever we look for a product on Amazon [145]. Google deduces the user's interests and recommends products based on those interests using multiple machine learning techniques. Likewise, when we use Netflix, we receive recommendations for series of entertainment, movies and other contents, which is also based on machine learning.

3.5.5 Self-driving automobiles

Self-driving cars are one of the most intriguing machine learning applications [146]. In self-driving automobile, machine learning plays key roles. Tesla, the well-known automobile manufacturer, is developing self-driving vehicles. It trains automobile model to recognise people and object while driving using an unsupervised learning method.

3.5.6 Medical diagnosis

In medical science, machine learning is used to diagnose disorders [147, 148]. Therefore, medical technology is evolving rapidly, and 3D model that can predict the exact lesions location in the brain is now possible. It facilitates the brain cancers detection and other brain-related illness.

3.5.7 Automatic language translation

Machine learning aids in translation by transforming text into familiar language. This feature is provided by Google Neural Machine Translation (Google's GNMT), a Neural Machine Learning that translates text into native language automatically. Sequence-to-sequence learning methods are the technology behind automatic translation, coupled with translation of text from one language to another and picture recognition.

3.6 Limitations of machine learning

Machine learning has proved transformative in several domains, yet it frequently fails to produce the promised outcomes [149]. There are various reasons for this, including a lack of (appropriate) data, data access issues, data bias, privacy issues, poorly designed tasks and algorithms, incorrect tools and personnel, a lack of resources and evaluation issues [150]. In 2018, an Uber self-driving car failed to identify a person, and the pedestrian (Elaine Herzberg) was killed due to the incident [151, 152]. Even after years of effort and billions of dollars, IBM Watson's attempts to employ machine learning in healthcare failed to deliver [153]. Machine learning has been utilised in updating evidence concerning systematic reviews and increased reviewer concerns due to the biomedical literature development. When students 'learn the wrong lesson', they can be disappointed. An image classifier trained just on photographs of brown horses and black cats, for example, may conclude that all brown patches are most likely horses [106]. In the real world, unlike people, existing image classifiers frequently do not make decisions based on the spatial relationships between picture component and instead study associations between pixels that human is unaware of but correlates with specific sorts of image of real object. Modifying this pattern on lawful images can cause the algorithm to misclassify the image as 'adversarial' non-linear systems, or non-pattern disturbances can potentially lead to adversarial vulnerabilities. Several systems are so fragile that single change hostile pixel causes misclassification.

3.7 Ethics of machine learning

Machine ethics (also known as machine morality, computational morality or computational ethics) is a branch of artificial intelligence ethics concerned with enhancing or ensuring the moral behaviour of man-made machines that employ artificial intelligence, also known as artificial intelligent agents [154, 155]. Privacy and surveillance, bias and discrimination and perhaps the deepest, most difficult philosophical question of the era, the role of human judgement, are three major ethical concerns for society, according to Sandel, who teaches a course on the moral, social and political implications of new technologies [156, 157].

3.8 Hardware of machine learning

More effective techniques in training deep neural network (machine learning specific subdomain) that incorporate various non-linear hidden unit layers have been developed since the 2010s, thanks to developments in computer technology and machine learning algorithms [158]. By 2019, GPUs had supplanted CPUs as the most common way of training large-scale commercial cloud AI, frequently with AI-specific upgrades [159]. From AlexNet (2012) to AlphaZero (2017), OpenAI calculated the amount of hardware computing required in large deep learning project and discovered 300,000-fold increase in the required computing amount, with 3.4-month doubling-time trendline [160].

There are embedded machine learning and neuromorphic or physical neural networks.

3.8.1 A physical neural network

A physical neural network also known as a neuromorphic computer, is an artificial neural network in which an electrical changeable substance emulates the neural synapse function. The term 'physical' neural network refers to physical hardware to simulate neurons rather than software-based techniques. Other artificial neural networks that use memristor or other electrical adjustable resistance materials to imitate neural synapse are also known as memristor networks [161, 162].

3.8.2 Embedded machine learning

Embedded Machine Learning is a sub-field of machine learning that uses embedded system with low computing capabilities, for instance, microcontrollers, wearable computers and edge devices to run machine learning models. Running machine learning models in embedded device eliminates the necessity to transport and store data on cloud server for processing further, resulting in fewer data breach and privacy leak and less theft of intellectual property, personal data and company trading secrets.

Embedded Machine Learning can be implemented using various methods, including hardware acceleration, approximation computation and machine learning model optimisation [163].

3.9 Software of machine learning

Different software suites having various algorithms have been used for machine learning. Some are free and open-source, and others are proprietary. The open-source and free software includes Caffe, ELKI, Deeplearning4j, Microsoft Cognitive Toolkit and DeepSpeed. However, KNIME and RapidMiner are the most popular open-source proprietary software [164], alongside R tool and Weka [165]. R tool is free and used for environmental statistics. RapidMiner is a complete data science platform focusing on delivering business value [166]. It brings together data preparation, machine learning and model operations to boost users' productivity of all skill levels within an organisation. The Konstanz Information Miner (KNIME) is a free and open-source platform for data analyses, reporting and integration [167]. Through its modular data pipelining 'Building Blocks of Analytics' concept, KNIME integrates multiple components for machine learning and data mining. The paid proprietary includes Angoss Knowledge STUDIO, Ayasdi, Amazon Machine Learning, IBM Watson Studio, Azure Machine Learning, IBM SPSS Modeler, Google Prediction API, Mathematica, KXEN Modeler, STATISTICA Data Miner, LIONsolver, Oracle Data Mining, MATLAB, Oracle AI Platform Cloud Service, Neural Designer, NeuroSolutions, SAS Enterprise Miner, Splunk, SequenceL, PolyAnalyst and RCASE.

4. Machine learning and biochar: past and the future

4.1 Classification of machine learning algorithms

For new users, selecting 'which algorithm to study' can be tough. Machine learning algorithms have their own set of advantages and disadvantages. Some excel with textual data, others excel at visuals and others at other data types. Many characteristics, such as resemblance, behaviour, data kinds and others, can be used to classify machine learning algorithms [168, 169].

Linear Regression, Logistic Regression, Decision Tree, SVM (Support Vector Machine) Algorithm, Naive Bayes Algorithm, KNN (K-Nearest Neighbours) Algorithm, K-Means and Random Forest Algorithm are some of the most used machine learning algorithms [170–172] as shown in **Figure** 7.

4.2 Machine learning algorithms used in biochar

Some selected works have been done using machine learning in biochar optimisation, which is dependent on the design of experiments for identifying pyrolysis parameters and optimising processes, which are all influenced by interconnected elements. The literature optimisation is separated into two categories: production and use. The optimisation procedure maximises the biochar's adsorption capacity and effectiveness for environmental and water remediation by antibiotics, extracting heavy metals and other contaminants from industrial effluent [174]. The three most significant process parameters in biochar manufacture are the heating temperature, heating time and heating rate [175]. The gaseous environment and particle size

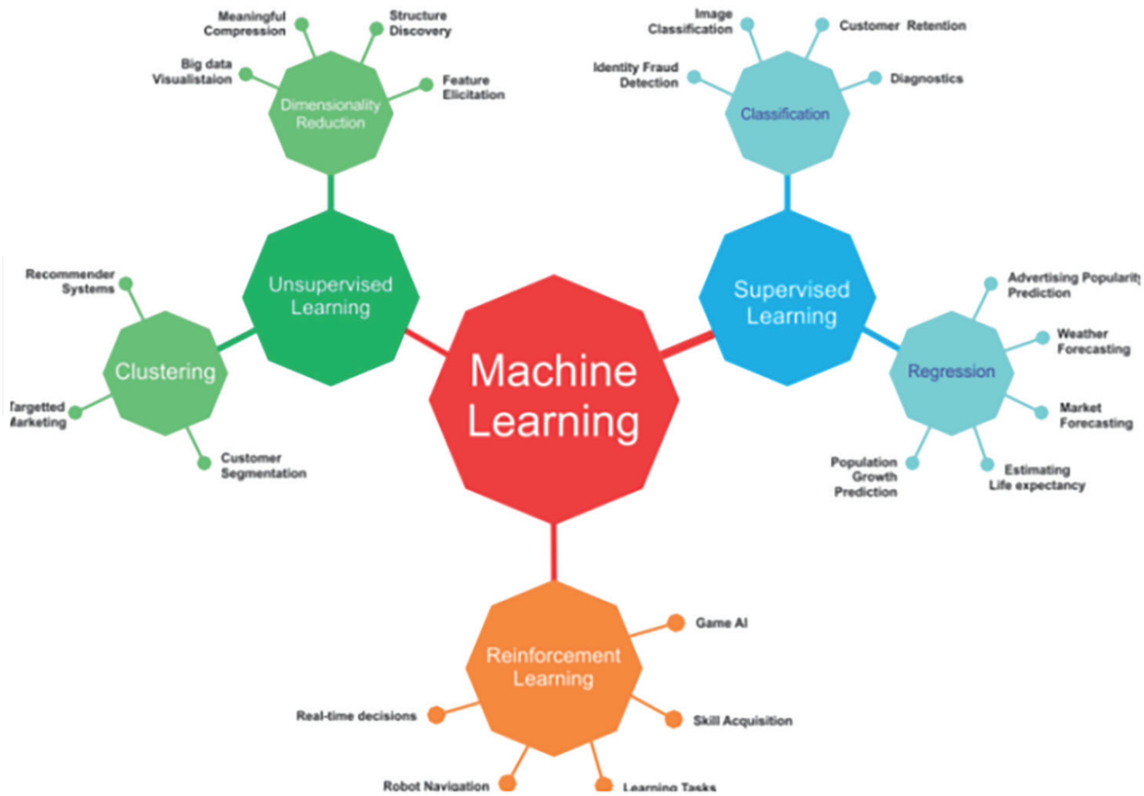

Figure 7.
Classification of machine learning algorithms [173].

employed in the biochar production variable such as the moisture contents, presence of inorganic/organic elements that catalyse certain reaction were included as feedstock factors for optimisation.

4.2.1 Yield prediction via machine learning

The algal biochar yield was predicted via extreme gradient algorithms. The XGB (eXtreme Gradient Boosting) machine-learning algorithm was used for prediction of algal biochar composition and yield in this study. In the XGB model, an intensive grid search strategy was designed to evaluate all of the available input parameter combination for forecasting biochar yield. Thirteen distinct pyrolytically significant input parameters combination were compared with the combination indicated by the model's techniques selection feature to predict biochar yield. The ash content, N/C, pyrolysis temperature, H/C and duration are essential parameters in determining the algal biochar output in this feature selection technique, where N, H and C are the nitrogen, hydrogen and carbon biomass content, respectively. Once the model was trained with the training data set, the highest R^2 of 0.84 was attained between model predictive and experimental biochar yield for the data set test. A Pearson correlation coefficients matrix showed the link between the biochar yield and input parameters. The Feature Temperature was the most significant element in plots. The interactive influence of other input parameter and temperature on algal charcoal output was represented using Shapley Additive exPlanations (SHAP) Dependence Plot. The plots' summary revealed the relevant features combined with SHAP and feature values.

The created XGB model adds to our understanding of the input parameter impact on algal biochar yield prediction.

Zhu et al.'s [176] machine learning was utilised in this study to construct prediction models for yield and carbon content of biochar (C-char) based on pyrolysis data of lignocellulosic biomass and investigate the inner information underlying the models. Based on biomass properties and pyrolysis circumstances, the results revealed that random forests could reliably forecast biochar output and C-char. Furthermore, for both yield (65%) and C-char, the proportional contribution of pyrolysis conditions was higher than that of biomass characteristics (53%). Structural information was more significant than element compositions for biomass characteristics for effectively estimating biochar yield, and the opposite was true for C-char. In the pyrolysis process, the partial dependence plot analysis revealed the impact of each important component on the target variable and the interactions between these elements. The study added the biomass pyrolysis process knowledge and improved biochar yield and C-char quality.

Sun et al. [177] studied the application of machine learning methods to predict metal immobilisation remediation by biochar amendment in soil. The work began by compiling and categorising data from published literature to develop a biochar soil remediation database, which now contains 930 data sets with 74 biochars and 43 soils. Then, based on biochar characteristics, soil physicochemical properties, incubation conditions (e.g. water holding capacity and remediation time) and the initial state of heavy metals, it modelled the remediation of five heavy metals and metalloids (lead, cadmium, arsenic, copper and zinc) by biochars using machine learning (ML) methods such as artificial neural network (ANN) and random forest (RF) to predict remediation efficiency. The ANN and RF models surpass the accuracy and predictive performance of the linear model ($R^2 > 0.84$). Meanwhile, the anticipated outputs of the models investigated model tolerance for missing data and interpolation reliability. Both the ANN and the RF models performed admirably, with the RF model having a higher tolerance for missing data. Finally, the contribution of factors employed in the model was assessed using ML models' interpretability. And the findings revealed that the type of heavy metals, the pH value of biochar and the dosage and remediation period were the most influential elements of remediation. The relative importance of variables could point researchers on the proper path for better heavy metal cleanup in soil.

Cao et al. [178] employed SVM (support-vector machine) approach for estimation of the biochar output from cattle dung pyrolysis in their study. The parameters employed for modelling were moisture content, pyrolysis temperature, biochar yield, biochar mass, sample mass and heating rate, and they were based on a data set of 33 experimental data. The following metrics were used to assess the performance: Magnitudes of root mean square error (RMSE), average percent relative error (APRE), average absolute percent relative error (AAPRE) and coefficient of discrimination (R^2). To compare the resilience and properties of SVM, an ANN model was created. Surprisingly, SVM outperformed ANN with an R^2 score of 0.9625, whilst ANN's R^2 value was 0.8040.

Li et al. [179] compiled information from prior studies to create a predictive model for biochar qualities depending on feedstock and pyrolysis settings. Though significant biochar properties such as pH, yield, specific surface area, cation exchange capacity, volatile matter content, ash content and elemental compositions are affected by different factors, there is strong link between biochar properties, feedstock type and pyrolysis temperature.

4.2.2 Distributing heavy metal via machine learning

Heavy metal testing using traditional spectral approaches is time-consuming and impossible to detect for huge amounts of effluent. Based on remote sensing imagery, geographical data and spatial distribution, machine learning algorithm may be utilised to forecast effluents metal distribution. RF, SVM and ANN have been used for this.

RF and ANN machine learning algorithm were utilised in predicting the heavy metals concentration present in soil using visible and infrared spectroscopy data [180]. Also, Zhang et al. [181] used geographical distribution data, and the concentrations of Cd, As, Cu, Zn, Pb, Cr, Hg and Ni in the soil were predicted via SVM, RF and ANN algorithms. Hu et al. [182] utilised RF to find the regulating factors in heavy metal bioaccumulation in soil-crop systems. ANN is a simple method for determining the link between the heavy metal pollutants removal and process parameter [133, 183].

4.2.3 Pyrolysis parameter

In recent literature, ANN has been primarily utilised to optimise pyrolysis parameters, but techniques such as the Taguchi approach have also been applied. This application creates orthogonal matrices using a basic statistical tool to conceptualise an integrated experimental design to discover crucial factors in an optimised operation [175]. For effective optimisation, ANN is employed in conjunction with other technologies. In Lakshmi et al. [126], a unique approach is described that combines several types of ANN in conjunction with techniques such as particles swarm optimisation to almost always guarantee global optimum without local minimum trapping. Particles swarm optimisation is novel, efficient, rapid, robust and simple when tackling non-linear, multi-variable problems. Razzaghi et al. [183] employ genetic algorithms to optimise the generated ANN, resulting in process parameter values.

4.2.4 Metal remediation and machine learning

Machine learning could be useful in developing predictive models for heavy metals cleanup utilising modified biochar. ML models are useful in the adsorption process because of their ability to analyse intricate correlations between factors [184]. ML models are an effective modelling tool in the adsorption process because of their capacity to improve analysed relationships among numerous parameters [185]. The performance of adsorption is affected by operational parameters such as heating rate, temperature, dosage, adsorbent surface area, particle size, starting concentration, pH and contact time value. Taking all of this into account, constructing adsorption models is time-consuming and takes a lot of experimentation. To avoid this tedium, ML can be used to create robust models in evaluating the heavy metals adsorption process [186–189].

Wong et al. [184] examined the operational parameters effect such as dosage, contact time, operating temperature and biochar initial concentration on the process of adsorption using rambutan peel biochar to remove Cu(II) from water body. They used AI models such as Multi-Layer Regression, ANN and ANFIS to study the impact of the above-mentioned operational parameters (MLR). Adaptive neuro-fuzzy inference system (ANFIS) is a Neuro-Fuzzy intelligent modelling and control technique for ill-defined and unpredictable systems. The system's input/output data pairs under examination form the basis of ANFIS. The ANFIS model was the most accurate, with 90.24% score, followed by 88.27% ANN and 59.14% MLR. For Pb(II) adsorption on ethylenediaminetetraacetic acid (EDTA) treated biochar, Li et al. [190] constructed an AI model utilising the SVM algorithm.

Nath and Sahu [155] employed iron oxides infused mesoporous rice-husk nano-biochar in removing arsenic. Using ANN and RSM methodologies, they obtained a removal efficiency of 96%. Six AI models was developed by Afridi [173] with different architectures network in ANN for prediction of heavy metal adsorptions on modified biochar. The six models were effective, with R^2 values greater than 0.99 between predicted and expected variables. Chakraborty and Das [191] developed an ANN model to estimate Cr (VI) absorption efficiency on sawdust biochar nanocomposite. The ANN model assisted them in determining an appropriate adsorption mechanisms and the most excellent feasible Cr (VI) equations for absorption on biochar modified.

Zhao et al. [192] demonstrated a new method to establish sensitive parameter impacting the process of adsorption and develop strong predictive model using AI. For prediction of the efficiency of six metal ions adsorption, the authors used kernel extreme learning machine, with SVM and Kriging model subset. These models accurately identified sensitive parameters, such as T, pH water, ionic radius, total carbon ratio and pH solute, with R^2 above 0.9, and could provide the necessary framework for developing predictive models for various scenarios.

Zhu et al. [193] investigated the application of machine learning methods to predict metal sorption onto biochars. The study used 353 data sets of adsorption studies from works of literature, the adsorption of six heavy metals (lead, cadmium, nickel, arsenic, copper and zinc) on 44 biochars was predicted using artificial neural networks (ANNs) and random forests (RF). The regression models were trained and refined to estimate adsorption capacity based on biochar properties, metal sources, environmental factors (temperature and pH) and the initial metal-to-biochar concentration ratio. The study discovered that RF model was more accurate than the ANN model.

Machine learning may be used to forecast and automate the remediation process and optimise process variables and feedstock conditions for optimal heavy metal removal efficiency. Machine learning may be utilised to create kinetic models and hybrid isotherm, which will accurately model for multicomponent systems and reduce error making the removal of heavy metal more cost-effective and efficient time.

5. Conclusions

The study was able to draw a relationship between biochar and machine learning. A review of biochar from history to application and challenges was discussed. Remediation of heavy metal is critical to avoid bioaccumulation, soil degradation and environmental contamination. Biochar is a practical and inexpensive method for removing heavy metal from waste effluent. Various approaches can improve the removal heavy metals effectively from pristine biochar. The paper also gave an overview of machine learning. Various algorithms of machine learning were discussed. After that, selected algorithms used for biochar were reviewed, and areas of opportunities were discussed. Artificial neural networks, support-vector models and random forests have been deployed in the machine learning of biochar. The ANN and RF models surpass the accuracy and predictive performance of the linear model. It was seen that random forest models perform better than artificial neural network models for predicting and generalisation. Machine learning will lead to a greater understanding of biochar's effectiveness and applications in more sectors.

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Conflict of interest

The authors declare that there is no conflict of interest.

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