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Review article

Recent advances in machine learning algorithms for sintering processes

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ABSTRACT

Machine learning (ML) is a fast-growing field that has vast applications in different areas and sintering has had no exemption from that. In this paper, the application of ML methods in sintering of the various materials has been reviewed. Based on our review, it was used to optimize the sintering process and improve the characteristics of the final product. For instance, a supervised learning algorithm was used to predict the temperature and time based on the raw material properties and the desired properties of the final product in sintering. Among all ML methods, k-nearest neighbor (k-NN), random forest (RF), support vector machine (SVM), regression analysis (RA), and artificial neural networks (ANN) had great applications in the sintering field. There are a limited number of papers that used deep learning in sintering. In conclusion, ML methods can be used to optimize sintering process in energy, cost and time.

KEYWORDS

Machine learning
Neural networks
Sintering
Classification
Materials

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1. Introduction

Sintering is a process of applying pressure or heat to a combination of materials, compacting them and forming a solid mass. It is a common process in the manufacturing industry, involving the heating and cooling of materials to form a solid mass. It is used in various fields such as metallurgy, ceramics, and powder metallurgy [1]. In recent years, machine learning (ML) tools have emerged as a powerful technology for optimizing the sintering process, improving product quality, and reducing costs. It is used to improve the efficiency and accuracy of various processes in manufacturing [2]. The application of ML in sintering processes is gaining more attention due to its potential to enhance the performance and quality of sintered products while reducing manufacturing costs. By analyzing large amounts of data, ML algorithms can identify patterns and relationships that can be used to optimize sintering conditions, predict material properties, and improve product quality. In this way, ML has the potential to revolutionize the sintering process, making it faster, more efficient, and more cost-effective [2].

In sintering, ML algorithms are utilized to optimize the parameters and improve the characteristics of the final product. Some examples of how ML can be applied in sintering include: 1) Predictive modeling: Supervised learning algorithms are used to predict the process temperature and time based on the raw material parameters and the desired properties of the final product. This helps improve the sintering process and the properties of the final product [3–5]. 2) Quality control: ML algorithms are used to cluster similar materials and identify patterns in the sintering data. This helps identify and correct any issues with the sintering process, such as non-uniform heating or cooling [6]. 3) Real-time control: Reinforcement learning algorithms are utilized to perform real-time controlling of the sintering process and make adjustments as needed to improve the properties of the final product [7]. 4) Microstructural analysis: ML methods are used to analyze the microstructure of the final product and identify any microstructural features that may be affecting the properties of the final product [8, 9].

In general, ML algorithms are used to optimize the sintering process, and make it a cost- and energy-effective process [10]. Some of the commonly used ML tools in sintering are: 1) Artificial neural network (ANN) [11]: It is a subgroup of ML methods that can learn complex patterns and relationships in data. In sintering, ANN can be used to

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anticipate the characteristics of the product based on the raw materials properties and process parameters. 2) Support vector machine (SVM) [12]: it is a type of supervised ML tool that is utilized for classification and prediction tasks. In sintering, SVM can be used to classify raw materials based on their properties and predict the properties of the final product. 3) Decision tree (DT) [13, 14]: In sintering, it is used to classify the materials based on their similarities or to predict the output material's properties or type. 4) Random forest (RF) [14, 15]: It is an ensemble learning tool that combines several DTs to improve prediction accuracy. In sintering, RFs are used to predict the quality of the final product based on multiple input variables. 5) Genetic algorithm [16, 17]: It is a type of optimization algorithm that is used to find the optimal values of process parameters. In sintering, genetic algorithms can be used to optimize the process parameters to improve product quality and reduce costs. 6) Deep learning [18–20]: It is used to improve the efficiency and quality of the sintering and to analyze the microstructure of sintered materials. By analyzing images of the microstructure, deep learning models can identify defects and predict the mechanical characteristics of the material. This information can be used to improve the design of sintered parts and to ensure that they meet the required specifications. Overall, the use of ML tools in sintering is still a developing field, and there is potential for further research and innovation in this area.

In this study, we review all the works that used ML tools to develop a new product and decrease the cost of production. In what follows, in method section we elaborate on search startegy, and the studies were investigated in this study. Next, we classified and synthezied the information inside these papers in the results and conclusion section.

2. Methods

2.1. Literature search

A comprehensive literature search was performed using different electronic databases, including Web of Science, Scopus, and Google Scholar. The search terms used were "machine learning", "artificial intelligence", "deep learning", "ceramics sintering", and "sintering process". The search was limited to articles published between 2010 and 2023. The articles were screened for relevance based on their title, abstract, and keywords. Inclusion Criteria were: 1) They were written in English, 2) They focused on the use of ML techniques in sintering, 3) They presented original research.

The Exclusion Criteria were as follows: 1) They were not related to sintering or ML, 2) They are conference papers, 3) They are review papers, and 4) They are not a full text. Fig. 1 demonstrates the searhc startegy of this study. Based on our search criteria, we could access to 100 papers. In the first screening stage, 40 papers excluded because of duplicate reports, non-English language, published before 2010 and were not full text. In the next screening stage, 21 papers were excluded as they were conference and review papers, and finally 5 more papers were removed from our collection since they did not use ML in sintering applications.

The papers that were reviewed are listed in Table1. Finally, 34 papers which met the inclusion and exclusion criteria were further analyzed and then data were extracted regarding the research aim and application, the type of ML techniques used, the sintering process parameters, the type of materials investigated, and the performance

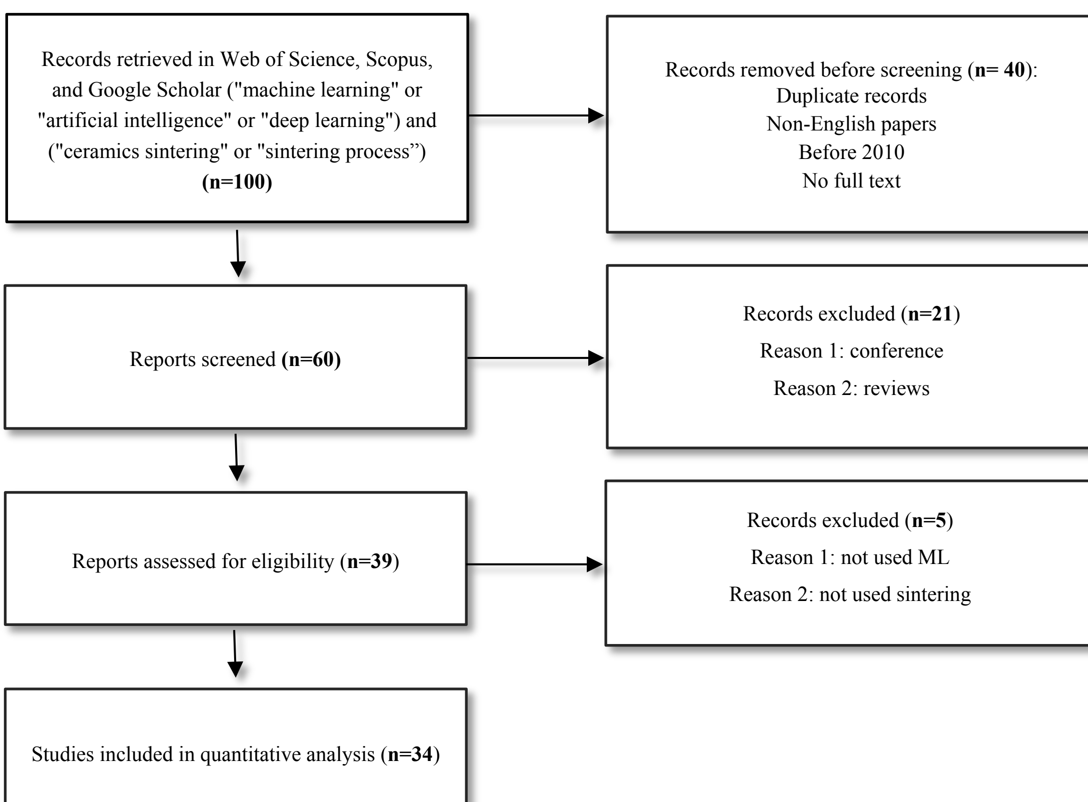

Fig. 1. The used search strategy to find related papers.

Table 1. Studies used ML for sintering.

Authors	Goal	Material	ML		
			Features	Type*	Performance
Mallick et al. [2]	Predict the productivity of sinter machine	Steel plant	Input: I/O fines, flux, sinter, drum TI Output: sinter productivity	LR and ANN	ANN is the best. Accuracy= 80%
Ly et al. [4]	Predict timing of bubble dissolution in SLS process	Bubble	Input: size of bubble and domain, diffusion coefficient, surface tension, viscosity, initial concentration, and chamber pressure Output: bubble dissolution time	EDT Bagged EDT Boosted	EDT bagged is the best. R^2= 0.988
Zhicheng et al. [5]	Predict the dimensional changes of metal samples made in sintering process	Low-cost metal Material extrusion	Input: layer thickness, sintering temperature, printing speed Output: length, width, height	LR, LRI, NN	NN is the best. R^2=0.999
Angalakuditi et al. [6]	Monitor the intensification process	Iron ore	Input: machine speed, green mix moisture, ignition temperature, and waste gas fan speed Output: TI	NN	R^2= 0.91
Jiang et al. [7]	Develop a model to find sintering parameters	Iron ore, limestone, coke	Input: slag, dolomite, Iron return fine, ash, limestone, sintering fine, quicklime, Added water Output: moisture	Offline deep learning and online self-learning NARX	NARX is the best. RMSE=2.01
Tang et al. [9]	Develop an ML tool that predicts the microstructure of materials	Alumina	Input: laser power Output: microstructure	RCWGAN‑GP	Good
Westphal & Seitz [10]	Classification of powder bed defects	SLS	Input: image Output: type of defect	VGG16 and the Xception CNN	VGG16 is the best. Accuracy=95.8%
Sahoo et al. [11]	To predict validation of physical properties of coke	Iron ore, coke	Input: physical parameters Output: validation	ANN	Accuracy=99.9%
Singh et al. [12]	Propose a method to maximize sintering productivity and quality	Iron ore	Input: ignition hood temperature, water flow rate, trimming flux, trimming solid fuel flow rates, strand speed, sinter bed height, suction pressure Output: TI, productivity, RDI	Stepwise regression, SVM, RF, MARS optimized by NSGA-II	RMSE (TI)=0.72 RMSE (RDI)=1.9 RMSE (productivity)= 3.02
Guo et al. [13]	Develop an ML model to assess if a metal structure can be manufactured from a given DMLS process	Metal cellular structures fabrication	Input: laser spot size, layer thickness, laser power, scanning speed, hatch distance, and maximum particle size Output: manufacturability	KNN, DT, RM, LR, SVM, MLP, SSDLMA	SSDLMA is the best. Accuracy= 78.5%
Kamal & Upadhyaya [14]	Show that prior prediction of density using an ML tool based on regression is an effective method	Bronze	Input: 12 features including powder characteristics, material composition, processing parameters Output: density	RF, LR, KNN, DT	RF is the best R2 over 0.9.
Ramos-Grez et al. [15]	Investigate feasibility of ML tool in estimating the steady-state temperature	Laser power	Input: heating-cooling parameters Output: temperature of surface	MLP, SVR, RF	MLR and RF are the best. R^2=0.98
Tang et al. [18]	Perform clustering and identification on a per-mine sample basis	Iron ore	Input: texture, geometric and grey scale features	CNN	Over 90%
Liu et al. [19]	Designing the whole sintering process	Mixture of flux, iron ore and coke	Input: process parameters Output: the number of sintering returned ore	Deep NN combined TCN & DF	R^2=98%
Kim & Zohdi [20]	Develop a deep learning tool to predict the optimal path of the SLS process	SLS	Input: tool path using programming Output: best laser path	CNN	Accuracy=93.9%
Li et al. [21]	Develop a burning state classification tool for sintering process	Rotary kiln	Input: gabor filter bank for texture analysis Output: burning state	ELM, MLP, PNN, SVM	ELM is the best. Accuracy= 92.75%
Chen et al. [22]	Develop a prediction model to define CCR for sintering	Iron ore	Input: time series of the CCR Output: CCR	RNN and JLNELN	Accuracy= 98.4%
Abdellahi et al. [23]	Predict porosity and strength of scaffolds	Scaffold	Input: pressure, Spacer concentration, type and size Output: porosity	GEP	Best R^2=0.96

Table 1. Continued.

Authors	Goal	Material	ML		
			Features	Type*	Performance
Wang et al. [24]	Develop a hybrid prediction model for sintering of iron ore	Iron ore	Input: 20 parameters (permeability, bed height, moisture, etc.) Output: TI, BTP, gas solid fuel consumption	ELM with AdaBoost.RT	Accuracy= 96%
Yuan et al. [25]	Develop a SDBN to predict quality-related features of a soft sensor	Steel	Input: pipes' pressure and temperature Output: FeO content	SDBN	RMSE= 0.009
Zhouzhi et al. [26]	Develop a method to predict sintering density of SiC	SiC	Input: heating rate, time and temperature history Output: density	DANN	MAE=0.13
Wie et al. [27]	Develop a method to design sintering processes	Artificial lightweight aggregates	Input: sintering time and temperature, and calcination time Output: density	LR, RF, and SVR	SVR is the best. Accuracy= 93.3%
Boidi et al. [28]	Develop a predictive model using experimental data	Textured and porous surfaces	Input: velocity and slide-roll ratio along with geometric characteristics of surface Output: CoF	RBF	R^2=0.935
Swaroop et al. [29]	Develop a ML tool to predict abnormal growth of grains in powdered samples	Powdered sample	Input: temperature, distance and FWHM of peaks, oxide matrix Output: abnormal growth	RF	Accuracy= 82%
Abreu et al. [30]	Model flash sintering process to predict the bulk density	Flash sintering	Input: holding time (TH) and electric current density (J). Output: density	ANN, KNN, RF, SVM	SVM is the best. R=0.62
Olanipekun et al. [31]	Predict hardness of laser-welded sintered stainless steel	Stainless-steel	Input: welding speed, welding temperature, sintering time, and sintering power Output: microhardness	ANN	Accuracy= 0.57%
Batabyal et al. [32]	Predict phase-field structure using a Gaussian process-based model	Selective laser sintering process	Input: 3 laser power setting and three different scanning speed settings Output: temperature distribution	Gaussian process regression	RMSE=1.2077
Kondarage et al. [33]	Develop an automatic X-ray image analysis approach	Glasses and ceramics	Input: density of the glass, diameter change of the struts	Fast RF for segmentation	Accuracy >88%
Ren et al. [34]	Predict strength of sinter drum	Sinter drum	Input: contents of Fe, FeO, SiO_2, MgO, CaO, and Al_2O_3 Output: strength	RM, SVR, NNR, RR	RF is the best. LR= 55.1%
Sadoun et al. [35]	Develop a ML tool to predict the impact of Al_2O_3 on the wear rates of Cu-Al_2O_3	Situ chemical technique	Input: wear load and speed Output: Al_2O_3 nanoparticles	RVFL using AHA	Accuracy= 99.55%
Fan et al. [36]	Develop a CNN for classification of sintered surfaces	Sintered surfaces	Input: images Output: sintered surfaces	CNN with HLWS Net+ Res HLWS	Accuracy= 95.1%
Jahan et al. [37]	Investigate the effect of processing parameters on defects	Powder bed fusion	Input: scan pattern, laser speed, and laser position Output: temperature	Graph-based ANN	-
Abdalla et al. [38]	Estimate the printability of SLS formulations	170 combinations of 78 materials	Input: composition and characterization from FT-IR, XRPD, DSC Output: printability	RF, LR, SVM, MLP, DT, KNN, Extr, GB, extreme GB	F1=81.9 improved to 88.9.

*SVM: Support Vector Machine, ELM: extreme learning machine, PNN: probabilistic neural network , MLP: Multi-layer Perceptron, BTP: burn-through point, CCR: comprehensive carbon ratio, RNN: Recurrent Neural Network, JLNELN: Joint Linear-nonlinear Extreme Learning Network, GEP: Gen Expression Programming, EDT Bagged: Ensemble Bagged Trees, EDT Boosted: Ensemble Boosted Trees, SDBN: supervised deep belief network, MARS: multivariate adaptive regression spline, TI: Thumber Index, RDI: reduction degradation index, NSGA-II: non-dominated sorting genetic algorithm II, DANN: domain-adversarial neural network, MSC: Master sintering curve, ECAS: electric current assisted sintering, NARX: exogenous, SVR: support vector regression, RBF: Radial Basis Function, CoF: Coefficient of Friction, SLS: selective laser sintering, ANN: artificial neural network, AGG: abnormal grain growth, FWHM: full width at half maximum, SSDLMA: semi-supervised deep learning based manufacturability assessment, DMLS: Direct metal laser sintering, LR: linear regression, LRI: linear regression with interactions, FT-IR : Fourier-transformed infrared spectroscopy, XRPD: X-ray powder diffraction, DSC: differential scanning calorimetry, GB: gradient boosting, TCN: convolution al network, DF: deep forest, NN: Nearest Neighbor regression, RR: ridge regression, RVFL: random vector functional link, AHA: artificial hummingbird algorithm, HLWS: Hybrid Lightweight Shunt Network.

obtained. The data collected from the selected articles was classified and analyzed using a narrative approach. In the results section, the findings were synthesized to provide an overview of the role of ML in the materials sintering.

2.2. Machine learning steps

In General, there are some steps involved in a typical ML workflow, including [40, 39]: 1) Data Collection: The first step is to collect and gather relevant data that will be used to train and test the ML model. This data can come from various sources such as public datasets, APIs, or internal databases. The number of data should be sufficient so that the performance could be high enough. 2) Data Preprocessing: Once the data is collected, it needs to be preprocessed to clean and prepare it for training the model. This includes tasks such as denoising, removing missing values, handling outliers, and scaling features. 3) Feature Engineering: This step involves selecting and transforming the relevant features or variables that will be used as inputs to the ML model. Feature engineering can improve the accuracy and performance of the model. To put it in other words, it is one way to select features that are the best representee of your data. 4) Model Selection: Choosing the right model and ML tool is critical for the success of a ML project. There are various types of models, such as regression, classification, and clustering, among others. The choice of model depends on the problem statement and the type of data available. 5) Training the Model: Once the model is selected, it needs to be trained using the preprocessed data. During the training process, the model learns from the input data and optimizes its parameters to make accurate predictions. 6) Hyperparameter Tuning: Hyperparameters are the settings of a ML algorithm that cannot be learned from the data, and they need to be tuned manually. Tuning the hyperparameters can improve the performance of the model. 7) Model Evaluation: After the model is trained, it needs to be evaluated using a test dataset to measure its performance. The evaluation metrics depend on the problem statement and the type of model used.

These are the general steps involved in a typical ML workflow. However, the actual process may vary depending on the problem statement, type of data, and the tools and technologies used. In the next section, we categorized the previous studies based of the type of ML tool, the performance parameter and the material used in sintering.

3. Results

Based on our finding, major applications of ML in sintering are: 1) Quality control: ML algorithms were used to predict the quality of the sinter based on the input raw materials and process parameters. This can help operators adjust the process parameters in real-time to optimize the sinter quality. 2) Process optimization: ML algorithms can be used to analyze large datasets of process variables and historical data to identify correlations and patterns. This can help optimize the sintering process to improve productivity, reduce energy consumption, and minimize waste.

3.1. Materials

According to our findings, ML has been used for various materials' sintering with the aim of optimization of sintering process including, iron ore fines, coke breeze, limestone, and other additives. The input materials used in ML applications will depend on the specific goals of the application, but they will typically include a combination of the following:

1- Iron ore fines: Iron ore sintering is a process in which iron ore fines are mixed with other materials, such as coke breeze, limestone, and other additives, and then agglomerated and heated in a sintering furnace to produce a porous, strong, and high-quality sinter [40]. ML algorithms can be used to predict sinter quality based on the properties of the iron ore fines, such as particle size distribution, chemical composition, and mineralogy [6, 12, 18].

2- Coke breeze: Coke breeze is a fuel and reducing agent used in sintering to provide the necessary heat and reduce the iron oxides [41]. ML algorithms can be used to optimize the amount and quality of coke breeze used in sintering to reduce energy consumption and improve sinter quality [7, 19].

3- Limestone: Limestone is a fluxing agent used in sintering to improve the properties of the sinter, such as its strength and porosity [42]. ML algorithms can be used to optimize the amount and quality of limestone used in sintering to improve sinter quality and reduce emissions [7].

4- Other metals and additives: some materials like bronze [14], steel [25], glass and ceramics [33] have applications in sintering as well and ML methods have been used to optimize their sintering process. Other additives, such as recycled materials, binders, and lubricants [9, 19], may also be used in sintering to improve sinter quality and reduce costs. ML algorithms can be used to optimize the use of these additives to improve sinter quality and reduce costs.

Based on reviewed papers, the materials mostly used in ML applications in sintering were a combination of iron ore fines, coke breeze, limestone, steel, bronze and other materials.

3.2. Database

To train the ML model, a large dataset of sintering process parameters and the corresponding materials' properties of the sintered objects is required. This data can be obtained through experiments, simulations, or a combination of both. In other words, the data can be real data in which we need to do experiments in the lab or simulated data whereby the data is produced by computers.

In experimental data, some sensors are used to monitor the sintering process and collect data on various parameters such as temperature, pressure, and gas flow rates. The sensors can be placed at different locations within the sintering furnace to obtain a comprehensive. Computational models are used to simulate the sintering process and predict the material properties of the sintered objects. These models can be based on a variety of methods, such as finite element analysis, molecular dynamics, or Monte Carlo simulations.

In either case, some input parameters are considered to feed into ML system. Based on our findings, these input parameters can be parameters related to 1) Chemical composition: The chemical composition of the raw materials used in sintering, including iron ore fines, coke breeze, limestone, and other additives, can have a significant impact on the properties of the resulting sinter. ML algorithms can be used to predict sinter quality based on the chemical composition of the raw materials. 2) Particle size distribution: The particle size distribution of the raw materials used in sintering can also have a significant impact on sinter quality. ML algorithms can be used to predict sinter quality based on the particle size distribution of the raw materials. 3) Operating conditions: The operating conditions used in the sintering process, including temperature, time, and gas composition, can also have a significant impact on sinter quality. ML algorithms can be used to optimize the operating conditions to improve sinter quality and reduce energy consumption. 4) Physical properties: The physical properties of the raw materials used in sintering, including density, porosity, and permeability, can also affect sinter quality. ML algorithms can be used to predict sinter quality based on the physical properties of the raw materials. 5) Weather and seasonal changes: The weather and seasonal changes can impact sintering production, for example, in terms of the moisture content of raw materials or operating temperatures. ML algorithms can help to account for these variations and their impact on sintering performance. 6) Features of images and signals: extraction of some features from images and signals that are representative of the data, can help to used advanced detailed features in ML.

Overall, the input parameters used in ML applications in sintering will depend on the specific goals of the application, nature, and type of the data. Mostly used parameters in ML with the application in sintering were parameters related to operating condition, particle size and composition of the sample. There were few studies that used features of images and signals related to the data.

3.3. Machine learning applications

There are so many ML methods that can be used in different applications. However, some specific ML algorithms are used to analyze the training data and develop a model that can predict the material properties of sintered objects based on the process parameters. These algorithms can be based on supervised or unsupervised learning, and include 1) SVM [12, 13, 30]: It is a powerful classifier that is particularly effective in handling high-dimensional data. It has been used in sintering applications for tasks such as predicting sinter strength and porosity. Based on our findings, it is one of the popular methods with good performance among researchers in sintering. 2) DTs [13, 14]: They are simple and interpretable classifiers that can handle both categorical and numerical data. They are very common and are used in sintering applications for tasks such as predicting the occurrence of sinter defects. 3) RFs [14, 15, 29, 30, 38]: They are an ensemble classifier that combines multiple decision trees to improve predictive performance. Hence, they have had a great application in sintering with the aim of predicting the quality of the sinter produced under different conditions. 4) ANN [5, 30, 31, 37]: It is a flexible classifier that can handle both categorical and numerical data and can learn complex relationships between input variables. As it can model nonlinear relationships between input and output, it has had a great role in the prediction of output materials based on the conditions of the experiment. 5) Gradient Boosting [38]: It is an ensemble classifier that combines multiple weak classifiers to improve predictive performance. It is used whenever other classifiers have not desired performance. Based on our results, a limited number of research studies have used this method by now. 6) RA [5, 13, 14, 32]: It is a statistical method used to model the relationship between a dependent variable and one or more independent variables. In the context of sintering, regression analysis can be used to predict the behavior of the sintering process based on various factors such as temperature, time, pressure, and composition. As it is one of the basic prediction methods, it has had a great application in sintering studies. 7) K-NN [13, 14, 30, 38]: It is a popular ML algorithm used in sintering. It is used to predict the mechanical properties, density, and other characteristics of sintered materials based on microstructural features such as grain size, porosity, and phase distribution. 8) Deep learning [11, 18, 20]: the specific type of it, convolutional neural network (CNN) has had application in sintering. In this method, the input of CNN is the figures of the samples. It is used to to develop predictive models that estimate the final properties of a sintered material based on its initial properties, sintering parameters, and other relevant factors or develop models for identifying defects or irregularities in the sintered material, based on visual or other measurements.

In conclusion, the choice of classifier in sintering will depend on the specific goals of the application, the nature of the data, and the desired balance between accuracy, interpretability, and computational efficiency.

3.4. Performance

There are several parameters have been utilized to measure the performance of ML tools [43]. The accuracy of an ML tool in sintering can be measured using various evaluation metrics, depending on the specific goals of the application. Some commonly used evaluation metrics in sintering applications include: 1) Mean Absolute Error (MAE) [44]: MAE is a common metric that measures the average absolute difference between the predicted and actual values. This metric is commonly used in regression tasks, such as predicting sinter strength or porosity. 2) Root Mean Squared Error (RMSE) [25]: RMSE is a metric that measures the square root of the average of the squared differences between the predicted and actual values. This metric is commonly used in regression tasks and penalizes larger errors more heavily than MAE. 3) Coefficient of Determination (R-squared or R^2) [4, 5, 14, 19]: R-squared is a metric that measures the proportion of variance in the predicted values that is explained by the input variables. This metric is commonly used in regression tasks and provides a measure of how well the model fits the data. 4) Classification accuracy [21, 24, 33, 35]: It is a common metric that measures the percentage of correctly classified instances. This metric is commonly used in classification tasks, such as predicting the occurrence of sinter defects. 5) F1-score [38]: It is a metric that balances precision and recall in binary classification tasks. It measures the harmonic mean of precision and recall and is commonly used when the classes are imbalanced. It has had a limited application in the sintering process ML.

To conclude, if an ML system has a low error rate (MAE and RMSE) and high accuracy, R^2 or F1-score, it has higher performance. The performance of an ML tool in sintering were often shown using R-squared, MAE, RMSE, and accuracy. Most studies reported either accuracy or MAE, RMSE, and R^2 at the same time. There was just one study that used the F1-score to demonstrate the performance of the developed ML tool. The choice of evaluation metric should be carefully considered to ensure that it aligns with the objectives of the application and provides a meaningful measure of performance.

4. Conclusions

This study provides a comprehensive overview of the current research on the role of ML in sintering. The article highlights the potential applications of ML in improving the efficiency and effectiveness of the sintering process and also making it a cost- and energy effective process. The findings of this review can serve as a foundation for future research in this field.

CRediT authorship contribution statement

Shahla Azizi: Conceptualization, Methodology, Resources, Writing – original draft, Writing – review & editing.

Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

Declaration of competing interest

The author declares no competing interests.

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