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Applications of artificial intelligence in engineering and manufacturing: a systematic review

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Abstract
Engineering and manufacturing processes and systems designs involve many challenges, such as dynamism, chaotic behaviours, and complexity. Of late, the arrival of big data, high computational speed, cloud computing and artificial intelligence techniques (like machine learning and deep learning) has reformed how many engineering and manufacturing professionals approach their work. These technologies offer thrilling innovative ways for engineers and manufacturers to tackle real-life challenges. On the other hand, the field of Artificial Intelligence (AI) is extensive. Several diverse theories, algorithms, and methods are available, which presents a challenge and a barrier in choosing the right AI technique for the appropriate engineering process or manufacturing process and environments. Besides, the pertinent literature is disseminated over various journals, conference proceedings, and research communities. Hence, conducting a systematic survey to scrutinise and classify the existing literature is worthwhile. However, it is challenging, but previous review studies have not adequately addressed AI's use and advancement in engineering and manufacturing (EM). Besides, some concentrated on single AI models, and others focused on a specific area in EM. This paper presents a comprehensive systematic review of studies on AI and its application in EM. To limit the scope of the current study, we conducted a keyword search in official publisher websites and academic databases, such as Springer, Elsevier, Scopus, Science Publication, Taylor & Francis, Directory of Open Access Journals (DOAJ), Association for Computing Machinery (ACM), Wiley online library, Inderscience and Google scholar. The search results (173 articles) were filtered according to a proposed framework, which resulted in ninety-one (91) relevant research articles. We reviewed the articles based on a proposed taxonomy (the year of publication, the AI algorithm and machine learning task adopted, the application area in EM, the train and test split of data, the error, and accuracy metrics used, the potential benefits). Our assessment using the proposed taxonomy gave a helpful insight into the literature's anatomy on various AI applications in engineering and manufacturing. Also, we identified opportunities for future research in AI application in the field of EM.

Keywords Artificial intelligence · Machine learning · Manufacturing process · Engineering process · Decision making

Introduction

The coming of artificial intelligence techniques has impacted our private lives and every engineering process. Areas such as manufacturing, industrial design, inspection, monitoring and control, repairs and maintenance of industrial assets, product testing and evaluation have received their fair share (Aggour et al., 2019; Varshney, 2016; Wuest et al., 2016). The ability of engineers to design, deliver and maintain state-of-the-art equipment and tools in the healthcare, insurances, energy, oil and gas, educations, aerospace, manufacturing and transportation industries have improved significantly in recent years with the help of artificial intelligence techniques (Aggour et al., 2019; Lechevalier et al., 2014; Stanisavljevic & Spitzer, 2016; Wang et al., 2018).

According to Aggour et al. (2019), reasoning computing techniques have immensely contributed to developing a more fuel-efficient and higher capacity aircraft in the aerospace and reducing asset downtime by swiftly recognising, alerting and fault rectification, thus, reducing overhaul time and costs. However, Aggour et al. (2019) pointed out

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that despite the wide-range application of AI in solving diverse engineering and manufacturing challenges, the world is still in the early stages of a higher industrial revolt driven by AI. Recently, AI techniques such as Deep Learning (DL) and ML make available unconventional analytics tools for examining and processing big manufacturing data challenging to achieve using conventional methods (Aggour et al., 2019; Wang et al., 2018).

AI algorithms have helped find solutions to domain-specific problems in different engineering fields (Hegde & Rokseth, 2020). Generally, it is established that AI helps reduce cycle time and scrap, which has tremendously enhanced resource use in specific complex problems in manufacturing (Bedbrook et al., 2019; Wuest et al., 2016). Additionally, it is argued that ML offers simple but compelling free tools for unceasing quality enhancement in a very complicated and challenging manufacturing process such as semiconductor design (Wuest et al., 2016).

Notwithstanding the benefits of AI techniques in engineering and manufacturing, Wuest et al. (2016) argue that its diversity poses a challenge to countless manufacturing practitioners and engineers regarding the proper technique to select from among the lots. Therefore, it might hinder the utilisation of AI techniques by an appreciable percentage of experts in this field. In closing this barrier, many studies attempted to provide a taxonomy of current advances in AI techniques (such as ML and DL) and their application in the field of EM to help manufacturing practitioners and engineers adopt the right AI tool for the right job. However, most of these existing systematic review studies surveyed the applications of a single AI technique, e.g., DL (Ardabili et al., 2020; Fujiyoshi et al., 2019). Otherwise, cover only one engineering or manufacturing domain, e.g., energy system (Mosavi et al., 2019), engineering risk assessment (Hegde & Rokseth, 2020), cutting processes in manufacturing (Cemernek et al., 2021; Preez & Oosthuizen, 2019), software development (Wen et al., 2012), minerals processing (McCoy & Auret, 2019), software fault prediction (Malhotra, 2015), glass science and engineering (Liu et al., 2021).

Thus, the progress and advancement of AI techniques (like ML and DL) in various engineering and manufacturing systems and environments have not yet been well addressed in the literature. Hence, a comprehensive systematic literature review of vital AI techniques applied in engineering and manufacturing is the study's primary objective. Specifically, this study seeks to:

1. Present readers and assist new researchers with a succinct summary of the terminology used in AI, a taxonomy of AI algorithms in EM, also identify trends in the use or research of AI techniques in EM.
2. Provide a wide-range and detailed assessment of previous state-of-the-art studies on AI techniques in EM; based on the year of publication, the algorithm and task adopted, the application area in EM, the train and test split of data, the error and accuracy metrics used.
3. Identify the challenges and opportunities in AI application to enhance and improve the EM processes.

We organised the remaining section of this paper as follows. Section 2 presents a brief description of AI and its associated techniques, such as machine learning and terminologies, and a summary of related review studies. Section 3 discuss in details the methods and materials adopted in this study. Section 4 presents the results and a detailed discussion of the study outcomes, and Sect. 5 presents the summary of findings and direction for future studies.

Artificial intelligence

Artificial intelligence (AI) is an extensive branch of computer science concerned with making a computer (machines), software or a computer-controlled robot perform tasks that typically require human intelligence or think intelligently. AI is an interdisciplinary science based on disciplines such as computer science, biology, psychology, linguistics, mathematics, and engineering, with multiple approaches. There are several ways to achieve AI, but ML is the most common way to go, and DL is a special type of ML. Moreover, ML and DL advancements create a paradigm shift in practically every sector of the technology, engineering, and manufacturing industries where AI is applicable.

Machine learning (ML)

According to Stanisavljevic and Spitzer (2016), ML provides approaches that can produce solutions for complex problems. ML enables systems and machines to learn automatically and improve from self-experience without being explicitly programmed. ML techniques are usually classified into four main groups, namely Supervised Learning (SL), Unsupervised Learning (UL), Semi-Supervised Learning (SSL) and Reinforcement Learning (RL) (Nti, Samuel, et al., Nti, Samuel, et al., 2019; Simeone, 2018; Stanisavljevic & Spitzer, 2016). In SL, the algorithm is fed with a labelled dataset (x, y) called training data, and based on this knowledge; a model is built. The model is then used to solve problems of the same kind, but this time for non-labelled data (Sharma, Kamble, et al., 2020; Sharma, Zhang, et al., 2020).

On the other hand, in UL, the algorithm is fed with an unlabelled dataset to build a model. The model then tries to identify the hidden patterns or extract futures from the given dataset. SSL algorithm provides a middle ground between

SL and UL, i.e., SSL combines SL and UL aspects into a thing of its own. In reinforcement learning, an ML algorithm interacts with an animated environment while carrying out actions toward realising the goal without a teacher's assessment if the completed actions are up-right or wrong (Stanisavljevic & Spitzer, 2016). RL algorithms are generally used for machine skill acquisition, robot navigation and real-time decision-making (Sharma, Kamble, et al., 2020; Sharma, Zhang, et al., 2020). Figure 1 shows the taxonomy of ML algorithms and their commonly used examples in the literature.

Basic ML system arrangement

Figure 2 shows a basic setup of the ML system. A learning objective is set, and based on it, a dataset (labelled or unlabelled) is collected from several data sources and partition into two (i.e., training-data and testing-data). Based on the organisational desire, the knowledge base decides on the ML algorithm, which best fit the current organisational goal. The knowledge learnt by the ML algorithm from the hidden pattern in the training data is applied to the test data (unknown data/example) to make the prediction. The model predicted

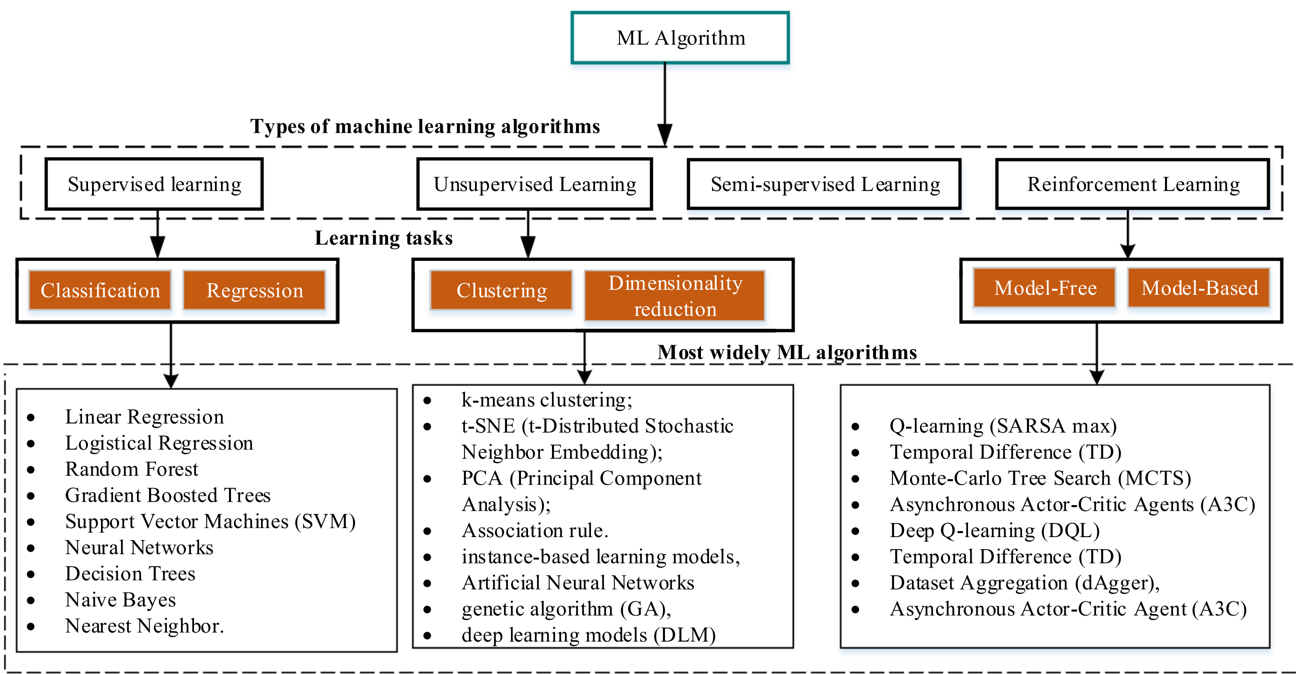


Fig. 1 Taxonomy of ML algorithms in the literature

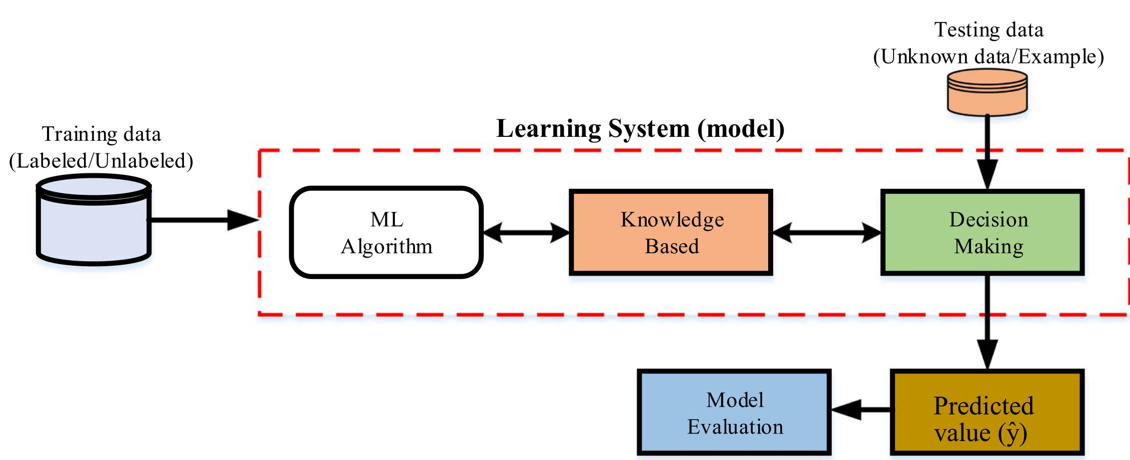


Fig. 2 A Basic ML system arrangement

output is compared with the desire values to measure the performance of the model.

Recently, ML techniques have been applied in more and more scientific fields such as financial analysis (Nti Adekoya, & Weyori, 2019, 2020; Nti, Appiah, et al., 2020; Sun et al., 2020), healthcare (Akyeramfo-Sam et al., 2019), energy, oil and gas (Damisa et al., 2019; Nti, Appiah, et al., 2020; Nti Adekoya et al., 2020; Nti Adekoya et al., 2020; Nti, Teimeh, et al., 2020; Nti, Samuel, et al., Nti, Samuel, et al., 2019), agriculture and food security (Akshatha & Shreedhara, 2018; Bagheri et al., 2020; Boateng, 2017; Nosratabadi et al., 2020; Nti et al., 2017), climatology (Arcomano et al., 2020; Guisiano et al., 2020), bioinformatics and biomedical (Naresh et al., 2020; Park et al., 2018; Shastry & Sanjay, 2020), learning and teaching (Liang et al., 2016; Nti & Quarcoo, 2019), robotics and autonomous driving (Bi et al., 2020; Chin et al., 2020; Fong et al., 2020), earthing resistance prediction (Nti Adekoya et al., 2020; Nti Adekoya et al., 2020; Nti, Appiah, et al., 2020; Nti, Teimeh, et al., 2020), quantum computing (Abbas et al., 2020; Zhao et al., 2019), building construction (Shen et al., 2020) and recommender systems (Panagiotakis et al., 2020). Table 1 gives a universal overview of the common terminologies in ML studies. While Tables 2, 3, 4 presents the different abbreviations and evaluation metrics used in ML studies as defined in the literature (Hegde & Rokseth, 2020; Hwang et al., 2012; Liakos et al., 2018; Mosavi et al., 2019; Nti, et al., 2019a; Sharma, Kamble, et al., 2020; Sharma, Zhang, et al., 2020). We grouped these abbreviations based on ML models (see Table 2), algorithms (see Table 3) and evaluation metrics (see Table 4), respectively.

Related studies

Table 5 presents a summary of review studies on machine learning applications in EM. We categorised these studies based on the number of papers reviewed, the publication period of papers, the searched database and study objectives. Based on Table 5, it is evident that previous studies have not adequately addressed the progress of AI and ML applications in EM. That is, as Ardabili et al. (2020), Elbes et al. (2019), Fujiyoshi et al. (2019) concentrated on single ML models; Fourati et al. (2020), Hegde and Rokseth (2020), Malhotra (2015), McCoy and Auret (2019), Mosavi et al. (2019), Preez and Oosthuizen (2019), Sacco et al. (2020) focused on a specific EM section. Such as in energy system, engineering risk assessment, cutting processes in manufacturing, software development, minerals processing or software fault prediction in engineering and manufacturing. Hence, there is a need for an organised, comprehensive systematic literature review that seeks to present the progress and advancement in ML application in EM systems and environment.

Table 2 Abbreviations for machine learning (ML) models

Model	Abbreviation
Support vector machines	SVMs
Dimensionality reduction	DR
Artificial neural networks	ANN
Deep learning	DL
Ensemble learning	EL
Bayesian models	BM
Decision trees	DTs
Instance-based models	IBM
Regression analysis	RA
Genetic algorithm	GA
Instance-based learning	IBL

Methodology

We adopted the systematic literature review (SLR) approach. We paid attention to reviewing the current published works in EM analytically; to obtain an unprejudiced and objective summary of the current state-of-the-art and future potential of AI and ML applications in EM. According to

Table 1 Commonly used ML terminologies

Term	Definition
Hypothesis set	Set of functions used for mapping a set of parameters/features
Loss function	A function for computing the difference between actual value (label) and predicted value by the model
Example	An instance of the dataset used for the ML process
Label	Value(s) allotted to an example
Hyperparameters	These are learning parameters specified to the ML algorithm
Parameter/feature	A set of traits/attributes/characteristics (or) vector associated with an example
Training sample	Examples/instances used for training the ML algorithm
Test sample	Examples/instances used for assessing the performance of the ML algorithm
Validation sample	Examples/instances used for parameters turning of the ML algorithm

Table 3 Abbreviations for ML algorithms

Algorithm	Abbreviations
Adaptive-neuro fuzzy inference systems	ANFIS
Principal component analysis	PCA
Bootstrap aggregating	Bagging
Extreme learning machines	ELMs
Random forest	RF
Bayesian belief network	BBN
Multiple linear regression	MLR
Back-propagation network	BPN
Classification and regression trees	CART
Expectation maximisation	EM
Deep belief network	DBN
Locally weighted learning	LWL
Radial basis function networks	RBFN
Chi-square automatic interaction detector	CHAID
Mixture of Gaussians	MOG
Partial least squares regression	PLSR
Convolutional neural networks	CNNs
Self-adaptive evolutionary-extreme learning machine	SaE-ELM
Multi-layer perceptron	MLP
Least squares-support vector machine	LS-SVM
Counter propagation	CP
Ensemble neural networks	ENNs
Support vector regression	SVR
Multivariate adaptive regression splines	MARS
Linear discriminant analysis	LDA
Deep Boltzmann machine	DBM
Ordinary least squares regression	OLSR
Learning vector quantisation	LVQ
Supervised Kohonen networks	SKNs
Generalised regression neural network	GRNN
K-nearest neighbour	KNN
Gaussian Naive Bayes	GBN
Successive projection algorithm-support vector machine	SPA-SVM
Self-organising maps	SOMs
Particle swarm optimisation	PSO

Cook et al. (1997), cited in Sharma, Kamble, et al. (2020), Sharma, Zhang, et al. (2020), SLR uses a proven scientific and replicable technique for accessing and understanding all the existing relevant research to a topic question or phenomenon of interest. Also, Kamilaris and Prenafeta-Boldú (2018) pointed out that SLRs help researchers develop relevant insights based on the hypothetical synthesis of previous and current research and find potential gaps in the literature. A three-stage SLR technique approach (i) pre-operational ("review planning"), (ii) operational stage ("carrying-out the review), and (ii) post-operational stage ("review findings") discussed in Tranfield et al. (2003) and verified by Ardabili et al. (2020), Mosavi et al. (2019), Sharma, Kamble, et al. (2020), Sharma, Zhang, et al. (2020) was adopted for this study. We discussed the details in the subsequent section of this study.

Within the EM processes, several areas use AI to offer adequate safety, an effective and efficient environment. Many research works have been conducted to enhance the EM processes using AI. We aimed to study the application of AI and ML techniques in EM; specifically, we focus on the AI and ML methods discussed above (see Table 3). We sought to comprehend and appreciate how machine AI and ML methods will help make the EM processes and systems safer and more efficient. To limit the scope of this paper, we conducted a keyword search in official publisher websites and academic databases, such as Springer, Elsevier, Scopus, Science Publication, Taylor & Francis, Directory of Open Access Journals (DOAJ), Association for Computing Machinery (ACM), Wiley online library, Inderscience and Google scholar. Our keyword search was guided by Lage Junior and Godinho Filho (2010) proposed literature review guide, which was tested by Jabbour (2013), explicitly, the following keywords were used in our searches: (i) artificial intelligence in engineering, (ii) artificial intelligence in manufacturing, (iii) computer-aided manufacturing, (iv) machine learning application in engineering; (v) smart manufacturing, safe engineering with AI.

Figure 3 shows the study framework for selecting the relevant papers. One hundred seventy-three (173) papers were downloaded; all papers were read entirely to ensure that they were within the scope of this study. Out of the 173 papers, nineteen (19) were duplicates, and fifteen (15) papers not published in English were removed, leaving 139 records shortlisted for the screening stage. Four (4) records that were found to overlap and three papers (newspaper articles and webpages) were also omitted; this reduced eligible papers for our qualitative analysis to one hundred and thirty-two (132). Of the 132, eighteen (18) papers (review studies on AI and ML applications in EM) and 23 papers (AI and ML applications in fields either than EM) were further excluded. Therefore ninety-one (91) papers were finally used in the quantitative analysis of our SLR.

Results and discussions

The final selected papers for our SRL were 91 (see Fig. 3). We present in details the study results and discussion in the following sections.

Descriptive statistics

Table 6 shows the distribution of reviewed papers per publication type. It was observed that most studies on AI

Table 4 Generally used evaluation metrics for ML models

Abbreviation	Evaluation metric	Definition
Root mean squared error	RMSE	$RMSE = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}\left(t_i - y_i\right)^2\right)}$
Mean absolute error	MAE	$MAE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{t_i - y_i}{t_i}\right\rvert$
Mean absolute percentage error	MAPE	$MAPE = \frac{1}{n}\left(\sum_{i=1}^{n}\left\lvert\frac{t_i - y_i}{t_i}\right\rvert\right)$
Nash–Sutcliffe coefficient radius	NS	$NSE = 1 - \left\{\frac{E\left(t_i - y_i\right)^2}{E\left(t_i - \bar{y}_i\right)^2}\right\}$
Relative percentage difference	RPD	$RPD = \left\{\frac{\lvert\left(x_2 - x_1\right)\rvert}{\frac{1}{2}\left(x_2 + x_1\right)}\right\}$
Area under the curve	AUC	$AUC = \int_0^1 \frac{TP}{(TP+FN)} d\frac{FP}{(FP+TN)} = \int_0^1 \frac{TP}{P} d\frac{FP}{N}$
Normalised mean squared error	NMSE	$NMSE = \left(\frac{\left(\sum_{j=1}^{N-1}\left(\text{target}_j - output_j\right)^2\right)}{\left(\sum_{j=1}^{N-1}\left(output_j - output_{j+1}\right)^2\right)}\right)$
Mean squared prediction error	MSPE	$MSPE = \left(\frac{1}{n}\sum_{i=1}^{n}\left(\vartheta_i - \hat{\vartheta}_i\right)^2\right)$
Root mean square prediction error	RMSEP	$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\vartheta_i - \hat{\vartheta}_i\right)^2}$
Mean bias error	MBE	$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(t_i - y_i\right)$
Correlation coefficient	R	$R = \left(\frac{\left(\sum_{i=1}^{n}\left(t_i - \hat{t}\right)\times\left(y_i - \hat{y}\right)\right)}{\sqrt{\left(\sum_{i=1}^{n}\left(t_i - \hat{t}\right)^2 \times \sum_{i=1}^{n}\left(y_i - \hat{y}\right)^2\right)}}\right)$
Accuracy		$Accuracy\,(\%) = \left(\frac{(TP+TN)}{(TP+FN+FP+TN)}\right) \times 100$
Precision		$PRE = \frac{TP}{TP+FP}$
Recall		$REC = \frac{TP}{TP+FN}$
Median absolute error	MedAE	$MedAE(y, \hat{y}) = median\left(\lvert y_1 - \hat{y}_1\rvert, \ldots, \lvert y_n - \hat{y}_n\rvert\right)$

y_i = model predicted value, t_i is the actual value and n = total number of test data. Also *TP* number of true positive values, *TN* number of true negative values, *FP* number of false positive values and FN number of false negative values $\bar{y}_i$ is the benchmark method

application in EM were published in journals as compared with conferences, books, and reports. This revelation suggested that a high percentage of authors prefer making their finding public via journals than other mediums.

Figure 4 shows the publisher's wise distribution of papers reviewed; we observed that high-impact peer-reviewed publication houses such as Elsevier, IEEE, Springer, and Wiley had seen the need for research in AI applications in engineering and manufacturing. On the other hand, it shows that most authors in this field prefer to show the study outcomes in high ranked and peer-reviewed journals.

Figure 5 shows the publishing trends of papers based on AI application in EM from 2006 to 2020. The graph shows that the interest in research in this area within early 2000 was low compared with figures from 2018 to 2020. A sharp increase in the publication numbers in 2011 was observed; this increase in the number of works reduced within 2012–2013, went up in 2014 and declined in 2015/2016. Notwithstanding, progressively stable growth in the number of publications was observed from 2017. This increase can be attributed to several factors, such as the availability of big data and the power of available ML and DL tools in recent years. Meanwhile, the discrepancy in publications numbers over the years suggest imbalanced learning, a gap for future research.

Figure 6 shows the word cloud generated from the titles of the reviewed paper. The aim was to analyse the most used words in titles of AI applications in EM. All titles of the 91 selected papers were combined in a simple text file; we adopted the word cloud API and Python to remove all stop words like "the firstly", "is", and "and". We then lemmatise each word and plot the frequency. We observed that the top ten (10) commonly used words in formulating paper titles among researchers were learning, machine, manufacturing

Table 5 A summary of the related review of machine learning in engineering or manufacturing

References	Papers reviewed SP	Papers reviewed UP	Publication period	Searched database	Objectives
Hegde and Rokseth (2020)	291	124	NA	Scopus and Engineering Village	Presented an organised review of literature that used ML methods to assist in engineering risk valuation
Köksal et al. (2011)	NA	NA	1997–2007	NA	Undertake a review of data mining applications in the manufacturing industry
Wen et al. (2012)	2191	84	1991–2010	IEEE Xplore, ACM Digital Library, ScienceDirect, Web of Science, EI Compendex, and Google Scholar) and one online bibliographic library (BESTweb) DBLP, CiteSeer, and The Collection of Computer Science Bibliographies	The study presented a systematic literature review (SLR) of literature on the ML model for software development effort valuation
Mosavi et al. (2019)	2601	70	NA	Thomson Reuters Web-of-Science and Elsevier Scopus	Provides an extensive classification and review of relevant ML and deep learning models used in energy systems
Preez and Oosthuizen (2019)	NA	NA	2000–2017	NA	Investigated the various ML algorithms within the context of sustainable manufacturing
McCoy and Auret (2019)	NA	NA	2004–2018	Elsevier, ACS publications, Taylor & Francis, SAIMM Journal and IEEE	To provide a systematic review of ML applications in mineral processing to equipping industrial practitioners and researchers with structured knowledge of ML in the field of mineral processing
Malhotra (2015)	122	79	1991–2013	IEEE Xplore, ScienceDirect, ACM Digital Library, Wiley Online Library, Google scholar, SpringerLink and Web of Science	Carried-out a systematic review of studies that use the ML techniques for software fault prediction
Liu et al. (2021)	NA	122	NA	NA	A review of current studies in adopting ML to accelerate the design of new glasses with custom-made properties
Kim et al. (2018)	NA	109	NA	NA	Provides a systematic review and summary of Machining-processes using ML algorithms
Catal and Diri (2009)	NA	74	1990–2007	Empirical Software Engineering, IEEE Journal of Systems and Software, SIGSOFT Software Engineering Notes, Software Quality Journal and Software-Practice and Experience	Provides a systematic review of literature on software fault prediction with a specific focus on datasets, methods, evaluation metric and results
Ardabili et al. (2020)	NA	77	2010–2020	NA	Presents a review and evaluate DL and ML methods and their applications in managing, production, consumption, and environmental impacts of biofuels
Allamanis et al. (2018)	NA	NA	NA	NA	Undertake a review of recent papers on ML methods for scrutinising source code
Wang et al. (2018)	NA	126	NA	NA	Presents an extensive survey of generally used deep learning algorithms and their applications toward making manufacturing "smart."
Sharma, Zhang, et al. (2020), Sharma, Kamble, et al. (2020)	NA	NA	NA	NA	Investigate the role of AI in the paradigmatic shift in manufacturing
Sacco et al. (2020)	NA	66	NA	NA	Presents an all-inclusive literature review of ML application in composites manufacturing

Table 5 (continued)

References	Papers reviewed SP	Papers reviewed UP	Publication period	Searched database	Objectives
Fourati et al. (2020)		235	NA	NA	Give a basic overview of ML techniques currently applied to cellular networks
Fujiyoshi et al. (2019)	NA	26	1998–2018		Presents a summary of DL techniques in autonomous driving
Elbes et al. (2019)	111	NA	1995–2014	Scopus, Google Scholar, Springer, Web of Science, and IEEE Xplore	A comprehensive overview of PSO application in engineering and network applications

SP search papers; *UP* used papers; *NA* not applicable; *DL* deep learning

engineering, design, autonomous, approach, using, prediction and systems. From Fig. 6, it can be inferred that manufacturing, autonomous driving, and computer-aided design are the main application area of AI methods in EM. It was further observed that AI terminologies such as ML, neural network, reinforcement, deep learning, pattern, model algorithm were frequently used in paper titles (see Fig. 6). Concerning ML task, classification was observed as the most used term in titles of papers.

SLR outcome

Figure 7 shows our SLR framework for this study. Firstly (step 1), a paper is analysed for the type of ML technique used, namely supervised learning (SL), unsupervised learning (UL), semi-supervised learning (SSL) and reinforcement learning (RL). Secondly, (step 2), we assess the type of ML task carried out (classification, regression, clustering, dimensionality reduction and feature extraction) based on the ML algorithm adopted by the paper. Thirdly (step 3), we examine the application domain of the paper in EM. Because the application domain of a paper is not known before an examination, we represented the application domain as a set *(App)*, $\{App = (App_1, App_2, \ldots, App_k)\}$ in our framework, where $(App_1, App_2, \ldots, App_k)$ are the likely domain a paper can fall within. Lastly (step 4), the data splitting ratio (train dataset and testing dataset), the evaluation metric, and reported values are analysed. We present our SLR results and findings based on our taxonomy (see Fig. 7) of ML application in EM. Hence, our results are grouped in four phases, thus (1) type of ML algorithm, (ii) the ML task, (iii) the application domain of paper in EM and (iv) data splitting ratio and evaluation metrics. In addition to these four phases, we further present some of the available tools for carrying out ML application in EM.

Phase 1: type of ML algorithm

Figure 8 shows the distribution of papers and the type of ML algorithm used. We observed that a high percentage (77%) of ML application in EM were based on SL. For example, the following (Ahila et al., 2015; Alipour et al., 2017; Appiah et al., 2019; Borges Hink et al., 2014; Catalina et al., 2020; Chen, Han, et al., 2020; Chen, Leng, et al., 2020; Chen, 2006; Cho et al., 2020; Cortés Sáenz et al., 2015; Dao et al., 2018; Deng & Yeh, 2011; Ding et al., , 2011, 2012; Eliseeva et al., 2019; Fan & Liu, 2017; Feldmann et al., 2015; Fuge et al., 2014; Ghadimi, 2015; Gu & Chen, 2018; Hoermann et al., 2018; Kilundu et al., 2011; Kim et al., 2012; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Li, Ding, et al., 2017; Li, Ma, et al., 2017; Meidan et al., 2011; Milosevic et al., 2017; Moayedi et al., 2020; Mwedzi et al., 2019; Nutkiewicz et al., 2018; Parfitt & Jackman, 2020; Park et al.,

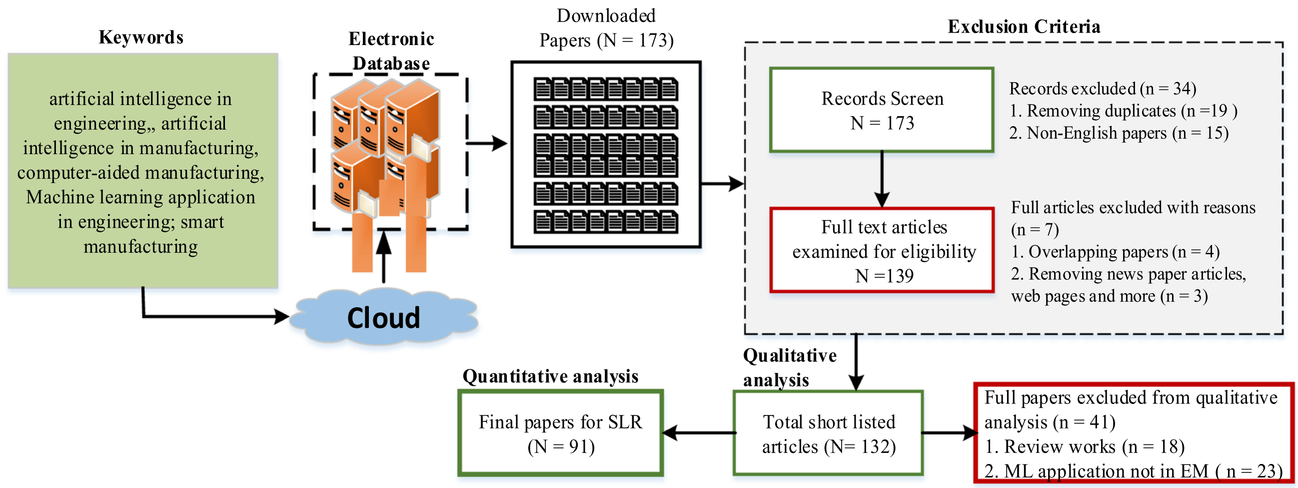


Fig. 3 Framework for paper selection

Table 6 Number of papers per publication type

Type of publication	No. of papers	%
Journal articles	68	75
Conference proceedings	21	23
Books & book chapters	1	1
Working papers and reports	1	1
Total	91	100

2016; Patel & Bhalja, 2016; Ravikumar et al., 2011; Reynen & Audet, 2017; Rudin et al., 2012; Shen et al., 2020; Shin et al., 2014; Subrahmanya et al., 2010; Tomin et al., 2015; Treml et al., 2016; Ward et al., 2018; Wei et al., 2017; Zhang et al., 2015) applied SL in their studies.

The high numbers of SL application in EM compared with other learning techniques can be partially attributed to the already labelled dataset's availability and SL lesser computational time than UL and RL. Again, in SL, the learning method typically happens offline compared with UL and RL that happens in real-time. Also, SL methods are highly accurate and trustworthy than UL. Of the 91 papers, 14% applied unsupervised learning technique (UL), that is (Ayawli et al., 2019; Fan & Liu, 2017; George, 2012; Kong, Fu, et al., 2020; Kong, Li, et al., 2020; Lei et al., 2016; Mo et al., 2021; Wuest et al., 2014) adopted the UL technique. On the other hand, 12% out of the 91 adopted semi-supervised learning. The following papers (Badesa et al., 2014; Kateris et al., 2014; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Reynen & Audet, 2017; Syafrudin et al., 2018; Veloso de Melo & Banzhaf, 2018; Wang et al., 2019; Wuest et al., 2014), while (Kateris et al., 2014) combine SL and UL technique.

However, according to El Sallab et al. (2017), reinforcement learning (RL) is a strong ML technique that can be

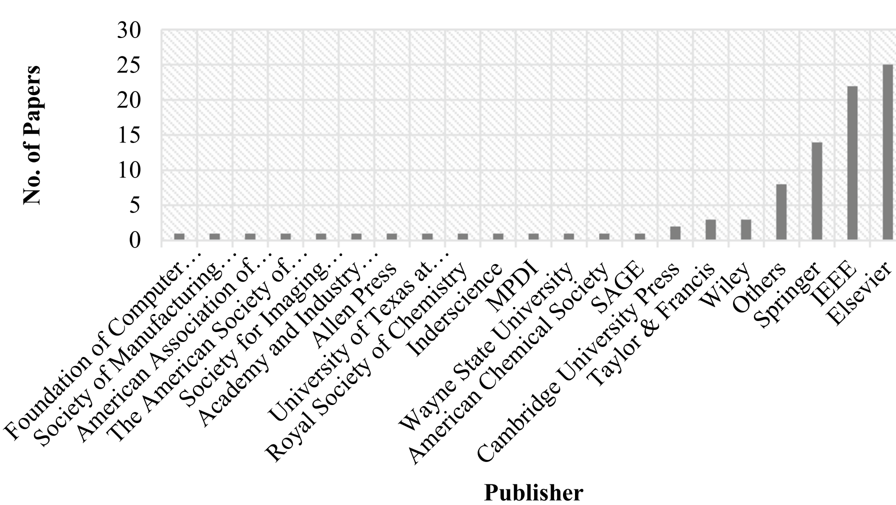


Fig. 4 Publisher wise publication

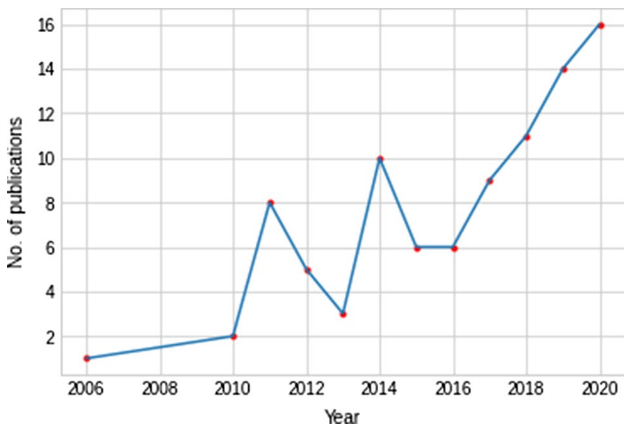


Fig. 5 Year-wise publication

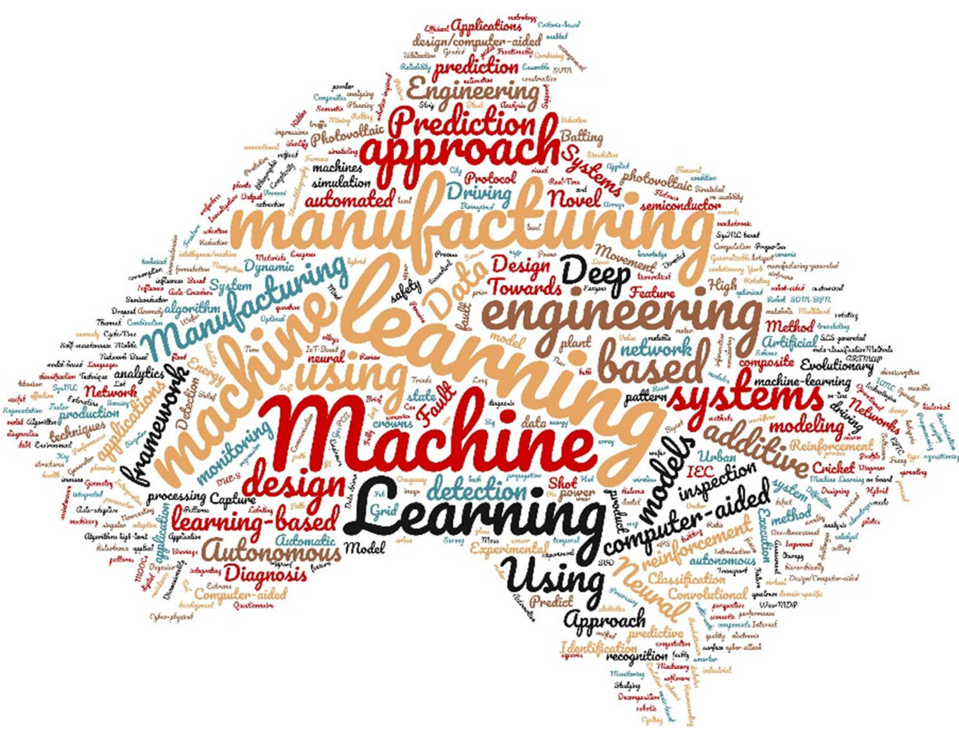
employed to efficiently teach machines (software or hardware) via interaction with their environment and learning from their mistakes. Recently RL techniques have been applied in several occupations, and EM cannot be exempted. From our SLR analysis, we observed that 6% (Mueller, 2017; El Sallab et al., 2017; Mackeprang et al., 2020; Rost & Schädle, 2013; Zhang et al., 2020) out of 91 studies adopted this technique.

Notwithstanding the high usage of SL in ML application, as shown in Fig. 8, Lei et al. (2016) pointed out that an intelligent diagnosis system based on SL methods primarily relies on manual extraction of features based on previous knowledge and diagnostic expertise. However, the recent upsurge of data (big data) in the engineering and manufacturing industries requires learning paradigm such as UL and RL. Their adeptness to rapidly and knowledgeably extract features and process collected data and signals to provide accurate diagnosis results autonomously makes them suitable. Lei et al. (2016) argument opens the door for feature studies in UL and RL techniques in engineering and manufacturing. Again, a confirmation of the current study (Mueller, 2017; Ayawli et al., 2019; El Sallab et al., 2017; Fan & Liu, 2017; Kong, Fu, et al., 2020; Kong, Li, et al., 2020; Lei et al., 2016; Mackeprang et al., 2020; Zhang et al., 2020) in this area focusing on UL and RL methods. Hence, we suggest UL techniques such as clustering and dimensionality algorithm, which can adequately handle complex and big data combined with conventional SL algorithms to improve machine accuracy in the future. However, it is essential to note that the high accuracy of most UL and RL is traded counter to higher computational costs, which in most cases makes them unsuitable for embedded devices.

Phase 2: ML tasks

As discussed already in this paper, several ML tasks are available, depending on the ML algorithm adopted. Figure 9 shows the percentage distribution of papers based on the ML task. It was observed that several of the ML application studies in EM were classification task (61%) (Ahila et al., 2015; Alipour et al., 2017; Appiah et al., 2019; Badesa et al., 2014; Borges Hink et al., 2014; Chen, Han, et al., 2020;

Fig. 6 A plot of selected papers titles



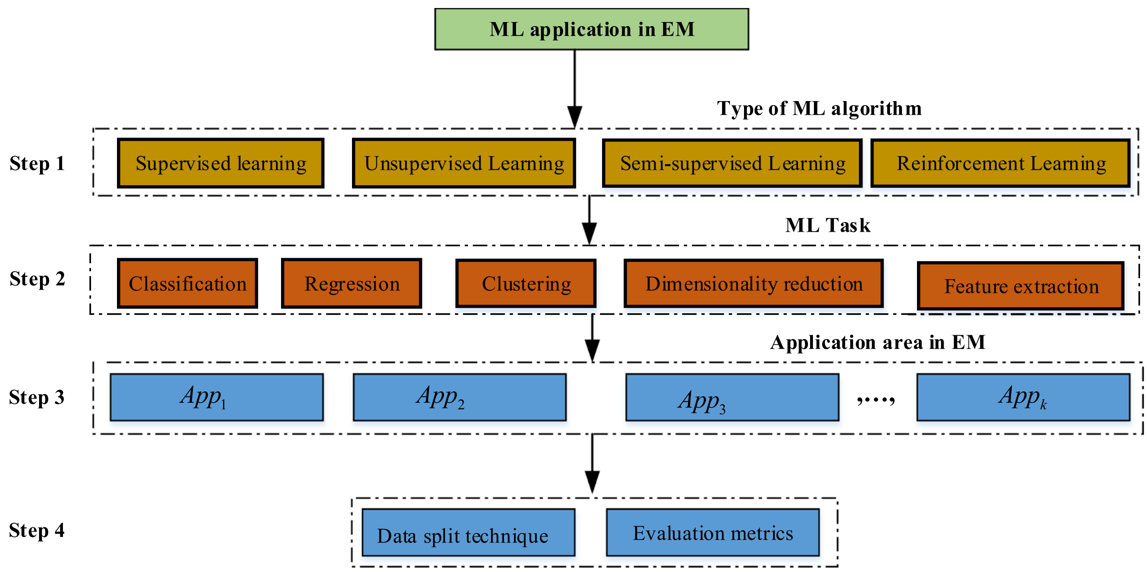


Fig. 7 Our SLR framework

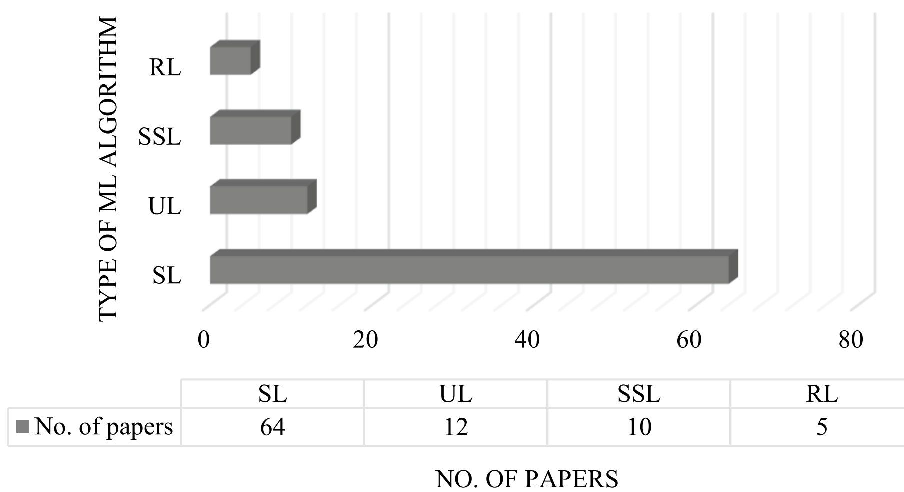


Fig. 8 Papers distribution across the various ML techniques

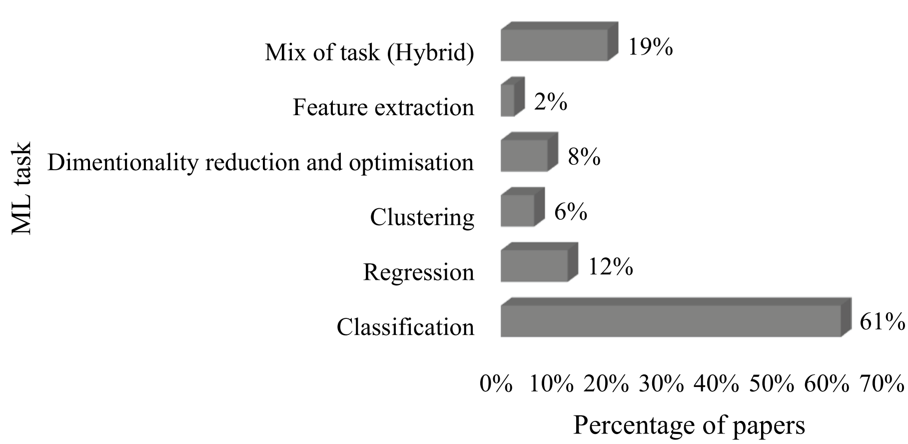


Fig. 9 Papers distribution based on ML task

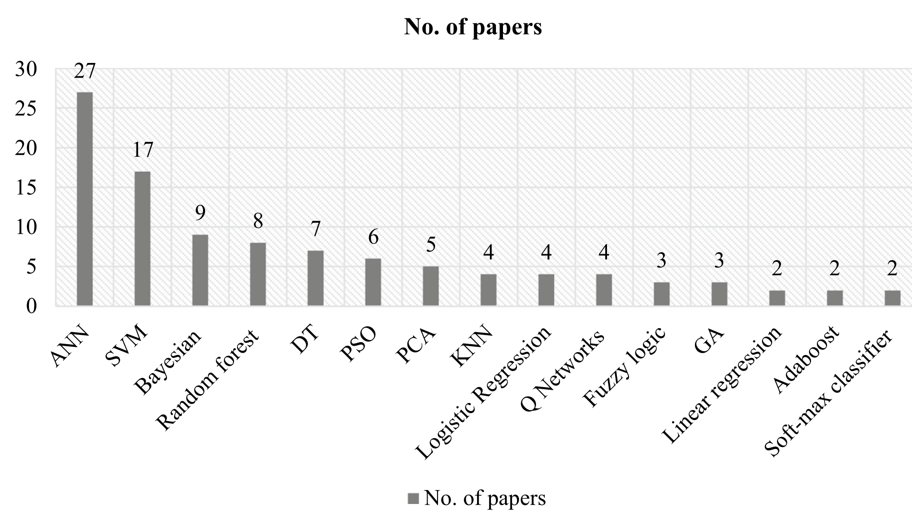
Chen, Leng, et al., 2020; Chen, Han, et al., 2020; Chen, Leng, et al., 2020; Chen, 2006; Cho et al., 2020; Cortés Sáenz et al., 2015; Ding et al., 2011, 2012; Eliseeva et al., 2019; Fan & Liu, 2017; Feldmann et al., 2015; Fuge et al., 2014; George, 2012; Ghadimi, 2015; Hoermann et al., 2018; Kilundu et al., 2011; Kim et al., 2012; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Meidan et al., 2011; Milosevic et al., 2017; Mwedzi et al., 2019; Park et al., 2016; Patel & Bhalja, 2016; Ravikumar et al., 2011; Reynen & Audet, 2017; Rudin et al., 2012; Shen et al., 2020; Subrahmanya et al., 2010; Tomin et al., 2015; Wei et al., 2017; Zhang et al., 2015). These results confirm the high number of studies (60/80) of ML application in EM adopting SL, as discussed earlier. 12% of papers (Catalina et al., 2020; Deng & Yeh, 2011; Gu & Chen, 2018; Li, Ding, et al., 2017; Li, Ma, et al., 2017; Nutkiewicz et al., 2018; Parfitt & Jackman, 2020; Shin et al., 2014; Wang et al., 2019; Zhang et al., 2017) were regression ML task. 8% were dimensionality reduction and optimisation (Badesa et al., 2014; George, 2012; Kateris et al., 2014; Reynen & Audet, 2017; Tam et al., 2019). In contrast, 6% (Ayawli et al., 2019; Fan & Liu, 2017; Kong, Fu, et al., 2020; Kong, Li, et al., 2020; Lei et al., 2016; Wuest et al., 2014) was based on clustering, 2% feature extraction (Chen, Han, et al., 2020; Chen, Leng, et al., 2020; Li, Zhang, et al., 2019; Li, Zou, et al., 2019). Notwithstanding, studies like Ward et al. (2018) adopted a mix of two or more of the ML task in their studies to achieved their set goal.

Depending on the ML task, several algorithms can be used. However, from papers reviewed in this study, we present a cross-section of commonly used ML algorithms applied in EM. Figure 10 shows the fifteen (15) most used ML algorithms applied in the EM. It is important to note that only ML algorithms used in at least two papers were included in this plot (Fig. 10).

We observed that the most used ML algorithm in EM application is the ANN (Appiah et al., 2019; Chen, 2006; Chen, Han, et al., 2020; Chen, Leng, et al., 2020; Lee et al., 2011; Lei et al., 2016; Li, Ding, et al., 2017; Li, Ma, et al., 2017; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Nutkiewicz et al., 2018; Shen et al., 2020; Shin et al., 2014; Wang et al., 2019; Zhang et al., 2017), such as CNN (Aziz et al., 2020; Gu & Chen, 2018; Hoermann et al., 2018; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Mwedzi et al., 2019; Park et al., 2016), LSTM (Appiah et al., 2019), MLP and Deep neural network (Chen, Han, et al., 2020; Chen, Leng, et al., 2020; El Sallab et al., 2017; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Lu et al., 2017; Treml et al., 2016). Followed by the SVM (Cho et al., 2020; Deng & Yeh, 2011; Eliseeva et al., 2019; Fan & Liu, 2017; George, 2012; Patel & Bhalja, 2016; Zhang et al., 2015), Naïve Bayesian (Meidan et al., 2011; Ravikumar et al., 2011; Subrahmanya et al., 2010; Wei et al., 2017), Random forest (Parfitt & Jackman, 2020; Tomin et al., 2015), DT (Alipour et al., 2017; Milosevic et al., 2017; Ravikumar et al., 2011; Wei et al., 2017) and PSO (Ben Guedria, 2016; Regis et al., 2019; Tam et al., 2019). The remaining are Fuzzy logic (Cortés Sáenz et al., 2015; Ghadimi, 2015), GA (Veloso de Melo & Banzhaf, 2018), deep Q-Learning (Mackeprang et al., 2020; Zhang et al., 2020) and ensemble learning (Kong, Fu, et al., 2020; Kong, Li, et al., 2020). This outcome confirms other similar SLR works (Hegde & Rokseth, 2020; Köksal et al., 2011; Malhotra, 2015).

According to Tu (1996) cited (Hegde & Rokseth, 2020), ANNs require less proper statistical training to develop. Also, they have the skill to detect all probable relations between the input *(x)* and output *(y)* variables. Again it is stated in (Mosavi et al., 2019) that the noise-immunity and fault-tolerant nature of ANNs make them suitable for innately noisy data from energy systems. Based on this assertion, we believe that it might contribute to the high use of ANNs in the literature (see Fig. 10).

Fig. 10 Top 15 commonly ML algorithm applied in EM studies



On the other hand, some studies adopted hybrid techniques to harness the power in different techniques to compensate for specific techniques' weakness. To mention a few (Ahila et al., 2015; Badesa et al., 2014; Borges Hink et al., 2014; Catalina et al., 2020; Chen, 2006; Chen, Han, et al., 2020; Chen, Leng, et al., 2020; Ding et al., 2011; Fan & Liu, 2017; Fuge et al., 2014; George, 2012; Ghadimi, 2015; Kateris et al., 2014; Milosevic et al., 2017; Moayedi et al., 2020; Ravikumar et al., 2011; Syafrudin et al., 2018; Tomin et al., 2015; Veloso de Melo & Banzhaf, 2018; Wang et al., 2019; Ward et al., 2018; Wuest et al., 2014).

Despite the high rate of ANN application in EM, Patel and Bhalja (2016) applied an SVM for condition observation and fault diagnosis of induction motor and reported a 98.86% accuracy rate against 94.28% accuracy rate with ANN. Hence, there are no fast rules of superiority among ML algorithms. However, we believe that they are domain-specific. Thus, their performance may differ from one area of application to the other. This revelation also calls for a comprehensive comparative analysis of the various ML algorithms in the same domain application in EM. Furthermore, it is indispensable to note that various properties might come with diverse challenges and diverse degrees of difficulty when adopting a machine learning algorithm for any domain application.

Phase 3: AI application area in engineering and manufacturing

AI is driving innovation in the engineering and manufacturing industries. Table 7 shows the distribution of papers across AI application areas in EM, with the highest application area been fault diagnosis (28.9%), followed by manufacturing monitoring, cost, and power consumption (14.5%). The remaining are detailed in Table 7. Advanced technologies like deep-learning, reasoning, representation of knowledge, knowledge-driven probabilistic modelling, computer vision, augmented reality, data management and more, as discussed earlier in this study, have contributed to solving several domain problems in EM.

To list a few, fault diagnostics and malware detections (Appiah et al., 2019; Chen, Han, et al., 2020; Chen, Leng, et al., 2020; Cho et al., 2020; Kateris et al., 2014; Lei et al., 2016; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Lu et al., 2017; Milosevic et al., 2017; Mwedzi et al., 2019; Patel & Bhalja, 2016; Subrahmanya et al., 2010; Wei et al., 2017; Zhang et al., 2015). Anomaly detection and predictive maintenance (George, 2012; Kroll et al., 2014), power system disturbance, grid and cyber-attack discrimination (Ahila et al., 2015; Borges Hink et al., 2014; Feldmann et al., 2015; Parfitt & Jackman, 2020; Rudin et al., 2012; Tomin et al., 2015). Manufacturing monitoring, cost and power consumption (Cortés Sáenz et al., 2015; Deng & Yeh, 2011; Ghadimi, 2015; Li, Ding, et al., 2017; Li, Ma, et al., 2017; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Nutkiewicz et al., 2018; Shin et al., 2014; Syafrudin et al., 2018; Wang et al., 2019; Ward et al., 2018; Wuest et al., 2014; Zhang et al., 2017). Semiconductor and integrated circuit (IC) manufacturing (processing, inspection, and transportation times) (Ding et al., 2012; Kim et al., 2012), virtual reality and computer networks (Badesa et al., 2014; Fan & Liu, 2017). Robotics, autonomous computing and driving (Mueller, 2017; Chen, Han, et al., 2020; Chen, Leng, et al., 2020; El Sallab et al., 2017; Eliseeva et al., 2019; Hoermann et al., 2018; Rost & Schädle, 2013; Treml et al., 2016). Design and building construction (Fuge et al., 2014; Gu & Chen, 2018; Shen et al., 2020), production, and reliability assessment (Chen, 2006; Kong, Fu, et al., 2020; Kong, Li, et al., 2020; Meidan et al., 2011) and machine vision (Park et al., 2016; Ravikumar et al., 2011).

Despite several AI applications in different engineering and manufacturing areas, sectors like (i) Lithography hotspot

Table 7 AI application area in EM

APP	Description	No. of papers	(%)
App_1	Fault diagnostics	24	28.9
App_2	Manufacturing monitoring, cost, and power consumption	16	19.3
App_3	Robotics, autonomous computing and driving	9	10.8
App_4	Anomaly detection and predictive maintenance	6	7.2
App_5	Power system disturbance, grid, and cyber-attack discrimination	7	8.4
App_6	Production	6	7.2
App_7	Semiconductor and IC manufacturing	5	6.0
App_8	Machine vision	4	4.8
App_9	Fault diagnostics	5	6.0
App_{10}	Virtual reality and computer network	3	3.6
App_{11}	Design and building construction	3	3.6
App_{12}	Wear and tear monitoring	2	2.4
App_{13}	Lithography hotspot detection	1	1.2

detection and (ii) wear and tear monitoring recorded a low application rate of 1.2% and 2.4%. The low number of studies in these areas creates an open door for feature studies to focus on the way forward to enhance these two areas with AI technologies. The overwhelming studies in this field is an indication that AI techniques are the best solution to overcome some of the current key challenges and difficulties of sophisticated engineering and manufacturing systems, affirming (Wuest et al., 2016) studies. Even though AI techniques have been applied to several problematic engineering and manufacturing areas, only a few of these have matured in the public domain (literature). In future, we anticipate that AI techniques will have a more significant influence on industries and business globally.

Interestingly, the outcome in Table 7 disagrees with the word cloud (see Fig. 6) plot of the selected paper title. i.e., from Fig. 6, application area words like manufacturing, autonomous driving and computer-aided design were the most used in papers titles. In contrast, Table 7 shows that most studies were carried out around fault diagnostics. This contradiction shows that in searching for papers in any specific domain, one needs to focus beyond the paper titles and read, if not in full, the abstract for a better understanding of the paper's application domain.

Phase 4: adopted evaluation metrics, data splitting ratio

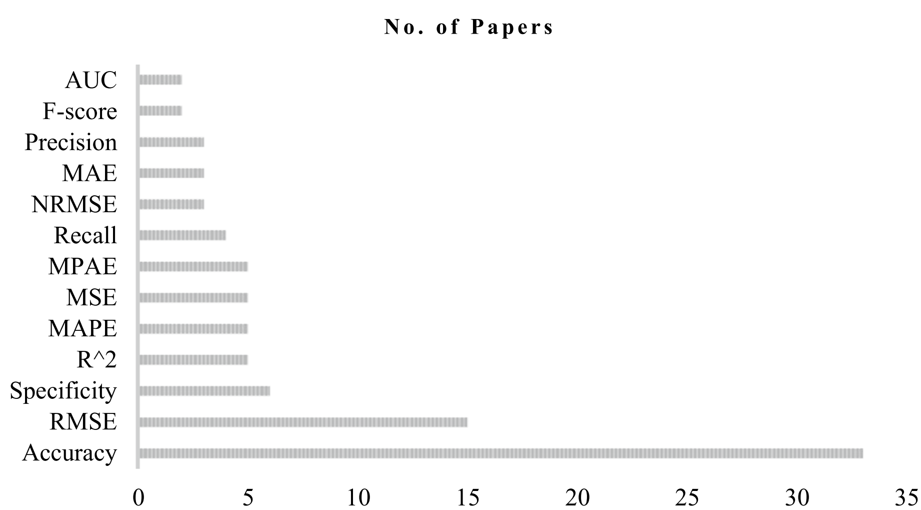
Adopted evaluation metrics

The assessment of a machine learning model is paramount in every AI setup. As already discussed (see Table 4), several evaluation metrics are available for assessing a machine learning model's efficiency and performance. The appropriateness of a metric for a machine learning model highly depends on the ML task. Figure 11 shows the percentages distribution of evaluation metrics that were adopted in at least two papers. We observed that the classification task studies usually adopted the accuracy metric (Ahila et al., 2015; Appiah et al., 2019; Chen, Han, et al., 2020; Chen, Han, et al., 2020; Chen, Leng, et al., 2020; Chen, Leng, et al., 2020; Cho et al., 2020; Ding et al., 2011, 2012; Fan & Liu, 2017; Feldmann et al., 2015; Kateris et al., 2014; Kroll et al., 2014; Lei et al., 2016; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Meidan et al., 2011; Mwedzi et al., 2019; Park et al., 2016; Patel & Bhalja, 2016; Ravikumar et al., 2011; Subrahmanya et al., 2010; Syafrudin et al., 2018; Ward et al., 2018; Wei et al., 2017) or RMSE and accuracy (Chen, 2006; Tomin et al., 2015; Zhang et al., 2017). On the other hand, regression task typically adopted MSE, RMSE, NRMSE (Deng & Yeh, 2011; Gu & Chen, 2018; Moayedi et al., 2020; Parfitt & Jackman, 2020; Zhang et al., 2020), MAE or MAPE (Nutkiewicz et al., 2018; Wang et al., 2019; Ward et al., 2018), F-score (Milosevic et al., 2017).

The results affirm the high number of ML application studies in EM adopting supervising ML algorithms for the classification task. Based on this study outcome, it can be concluded that the accuracy metric is the most suitable to use when performing a classification task. However, as argued in Nti et al. (Nti, Appiah, et al., 2020), Picasso et al. (2019), Xing et al. (2018), using a single statistical metric to evaluates a machine learning model is incomprehensive. Hence we advise the adaptation of multiple metrics where applicable, as done in these works (Chen, 2006; Tomin et al., 2015; Zhang et al., 2017).

Out of the 39% of papers that adopted accuracy metric, it was observed that 48% achieved model prediction accuracy within the range of (81–95)%, for example (Badesa et al., 2014; Chen, Han, et al., 2020; Chen, Leng, et al., 2020; Cho et al., 2020; Ding et al., 2011; Fan & Liu, 2017; Feldmann et al., 2015; Mwedzi et al., 2019; Patel & Bhalja, 2016; Ravikumar et al., 2011; Subrahmanya et al., 2010), 38% within

Fig. 11 The top (13) commonly used evaluation metrics for measuring the performance of ML models



(96–100)%, example (Borges Hink et al., 2014; Fuge et al., 2014; Kateris et al., 2014; Kroll et al., 2014; Lei et al., 2016; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Park et al., 2016; Syafrudin et al., 2018; Zhang et al., 2017) and 14% within (66–80)%, example (Chen, Han, et al., 2020; Chen, Leng, et al., 2020; Meidan et al., 2011; Ward et al., 2018).

These statistics show that more than half (52%) of studies in ML application in EM obtained an accuracy which is less than 95%. Therefore, any improvement in accuracy above 95% in this field is a significant enhancement. Hence, future works could look at ways to improve the accuracy closer to 100% in this field.

When it comes to data partitioning, we observed that the most typical partition ratio (80:20) (Deng & Yeh, 2011; Gu & Chen, 2018; Moayedi et al., 2020; Zhang et al., 2017), (65:35) (Kateris et al., 2014), (70:30) (Meidan et al., 2011), (75:25) (Li, Ding, et al., 2017; Li, Ma, et al., 2017) where the first figure id for training and second for testing. Besides, other studies adopted the train, validate and test data partition, papers like (Nutkiewicz et al., 2018; Reynen & Audet, 2017) adopted the (60:20:20) and (Fuge et al., 2014) used (80:10:10) partition format.

There is generally no acceptable rule for partitioning training, validation, and testing dataset; moreover, none of the reviewed papers gave any concrete rationale behind the adopted partition format used. However, from our perspective, we believe that the increase in the (80:20) division is foundered on the Pareto principle. Our partial search of the literature ((i) https://en.wikipedia.org/wiki/Pareto_principle (ii) https://towardsdatascience.com/train-validation-and-test-sets-72cb40cba9e7 (iii) https://stackoverflow.com/questions/13610074/is-there-a-rule-of-thumb-for-how-to-divide-a-dataset-into-training-and-validatio/13623707#13623707) shows that the Pareto approach is one of the best techniques out there for data partition in AI and ML studies. Hence novice in this field can adopt this technique (80:20) comfortable or use the in-sample and out-of-sample test technique to attain the optimal data splitting.

Selection of learning rate for ANN models

Typically, a neural network's convergent rate is vital since it contributes to computational cost. As points out in Chen, Han, et al. (2020)), Chen, Leng, et al. (2020)), a high-learning rate usually possesses difficulty in neural network convergence (unstable training or suboptimal solution), especially in situations where a small batch size is used network is training. Nevertheless, where the learning rate is meagre, the network might require several training epochs to attain convergence. If not well articulated, it can lead to longer hours of training and testing the model, leading to computational cost. We observed that most studies used fixed learning rate, e.g., 10^{-8} (Treml et al., 2016), 10^{-4} (Aziz et al., 2020; Zhang et al., 2017), 0.01 (Nutkiewicz et al., 2018), 10^{-3} (Chen, Han, et al., 2020; Chen, Leng, et al., 2020; Li, Zhang, et al., 2019; Li, Zou, et al., 2019; Mackeprang et al., 2020). In contrast, Appiah et al. (2019) used adjustable learning rates via a special algorithm, like Grid search, to obtain the best learning rate. The current study proposes that novice in this field can adapt the Grid search algorithm proven in the literature (Appiah et al., 2019; Li, Ding, et al., 2017; Li, Ma, et al., 2017) to help choose the right learning rate. Concerning the activation function, we observed that the linear function was the most commonly used in Mackeprang et al. (2020), Mwedzi et al. (2019), Nutkiewicz et al. (2018) and more.

Commonly used AI and ML modelling tools in EM

Several AI and ML modelling tools and platforms are available for any ML task; however, from our SLR, the commonly used ML modelling tools observed in EM are shown in Fig. 12. It is good to note that the order of hierarchy presented in Fig. 12 has nothing to do with their efficiency nor popularity.

Conclusions

Systematic literature review (SLR) is accepted as one way to examine what has been done and what needs to be added. The current study sought to perform an SLR of AI techniques application in engineering and manufacturing. However, unlike previous SLR studies that focused on single domain applications such as diagnosis, autonomous

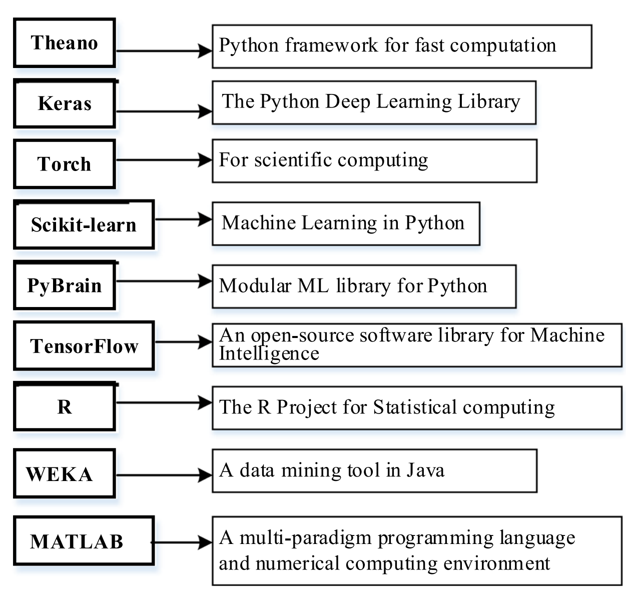


Fig. 12 Commonly used ML software and tool

driving, virtual reality, computer network or a single ML algorithm in this field, we provided a comprehensive SLR of AI applications in thirteen (13) different EM areas. We provided a taxonomy of previous studies into (i) type of ML algorithm used, (ii) ML task performed, (iii) EM application area, and (iv) the data splitting ratio and the evaluation method used. We also looked at common values and techniques for selecting the ANN learning rate and comparing reported accuracy. We aimed at (i) Presenting readers and assisting new researchers with a succinct summary of the terminology used in AI, a taxonomy of ML algorithms, and identifying trends in the use or research of ML techniques in engineering manufacturing. (ii) Providing a wide-range and detailed assessment of previous state-of-the-art studies on AI techniques in engineering and manufacturing and (iii) Identify the challenges and opportunities in AI for future enhancement and improvement in the engineering and manufacturing processes. We anticipated that this study's outcome would enable novice in applying AI in engineering and manufacturing and practising manufacturing and engineers to quickly come to grips with which AI techniques to use for a given environment or problem. Also, provide that with what has been done so far in the field and where improvement is needed. The following observations were made:

1. A very high percentage (77%) ML application in EM was based on supervised learning (SL), making SL technique common among machine learning techniques applied in EM. However, Lei et al. (2016) argue that SL methods mostly rely on manual extraction of features based on previous knowledge and diagnostic expertise. Hence, make them unappropriated in the era of big data where techniques are required to rapidly and efficiently extract features and process collected data and signals to provide accurate diagnosis unconventionally. Besides, their argument we support by the number of current studies (Mueller, 2017; Ayawli et al., 2019; El Sallab et al., 2017; Fan & Liu, 2017; Xiangyu Kong, Fu, et al., 2020; Kong, Li, et al., 2020; Lei et al., 2016; Mackeprang et al., 2020; Zhang et al., 2020) we observed applying unsupervised and reinforcement techniques in the field of EM. As a remedy, a combination of SL and UL techniques can be effectively adopted to improve traditional SL techniques in a single application.
2. Several ML application studies in EM were classification task (61%), and the most used AI algorithm was ANN, followed by SVM. Despite the high ANN technique among surveyed papers, Patel and Bhalja (2016) showed that SVM outperformed ANN on the same dataset. Hence, the high numbers in ANN among papers do not show its superiority among AI algorithms. On the other hand, we believe that AI algorithms are domain-specific. Therefore, there might be a difference in performance from one area of application to the other. Based on this, we advise that when selected any AI technique for any domain application, several properties that could affect its performance must be taken into accounts.
3. A high percentage of AI studies (28.9%) were applied in fault diagnosis than other domain areas in EM (see Table 7). On the other hand, few studies focused on lithography hotspot detection and wore and tore monitoring. Thus, 1.2% and 2.4%, respectively. However, several studies with AI in EM indicate that AI is the way forward in providing the best solution to overcome some of the current key challenges and difficulties of complex EM systems.
4. In terms of model evaluation, most studies adopted the accuracy metric compared with RMSE, MSE MAPE, recall, F-score and more. Only a few studies (Chen, 2006; Tomin et al., 2015; Zhang et al., 2017) adopted a combination of several accuracies and closeness metrics in their paper. Nevertheless, as argued in the literature (Nti et al., Nti, Appiah, et al., 2020; Picasso et al., 2019; Xing et al., 2018), adopting a single evaluation metrics in a data science application is not comprehensive, hence in going forward, future works can adapt of multiple metrics.

With sureness based on the study results, we can say that machine learning and deep learning techniques are currently among the powerful, intelligent tools used in smart manufacturing and engineering processes. Their importance is anticipated to intensify in the future. Also, the interdisciplinary nature of AI offers many opportunities. However, a significant risk is a collaboration between different disciplines, such as industrial engineering, information technology, electrical and mechanical engineering, computer science and mathematics, which is necessary to drive progress in this 21st era. Notwithstanding the promising results reported by this paper, there are still some opportunities for improvement in future works, as discussed in Sect. 4. However, as computing resources such as fog computing, cloud computing and more, computational intelligence like deep learning technology may be pushed into the cloud to enable a more convenient and on-demand computing service for the smart EM process.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any.

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