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Review

How can artificial intelligence impact sustainability: A systematic literature review

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A R T I C L E I N F O

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A B S T R A C T

We need a proper mechanism to manage issues related to our environment, economy, and society to proceed toward sustainability. Many researchers have worked for sustainable development goals using artificial intelligence (AI) and machine learning to develop an efficient mechanism to facilitate a circular economy and link up the needs of the present generation without disconcerting the capability of coming generations. This study offers a comprehensive review of AI and sustainability and suggested future research scope. The review has focused on different use cases in industries like construction, transportation, healthcare, manufacturing, agriculture, and water. The systematic review is based on 287 papers selected out of 8341 search results with an application of PRISMA based method. Out of all the techniques used in sustainability regression, RL and DSS-based AI models are more popular than others. The review also provides directions surrounding which industrial sectors are using which methods for incorporating sustainable development practices in their organization.

1. Introduction

With many nations are affected by climate change, environmental sustainability is becoming increasingly important to business operations worldwide. Sustainability is a standardized idea that focuses on the beat generation equity and is usually considered to have three aspects: the environmental, economic, and social dimension. Flourishing economies and environmental deterioration cannot coexist, as achieving environmental sustainability also entails risks that could have an impact on business operations and prospects in a fiercely competitive market (Patel, 2021). This idea can be used in making direct decisions at all the levels: at the international, national, and individual consumer level. World Meteorological Organization estimate a virtually 50/50 likelihood that pre-industrial levels of global average temperature may unexpectedly rise above 1.5 °C within five years (Alex Knapp, 2022). To tackle the situation, UNFCCC imposes basic standards for hosting a conference named as COP by considering agenda of meeting carbon neutrality. The UK Government committed to implementing the International Norm for Event Sustainability Management Systems (ISO20121) and the first COP to achieve PAS 2060 (Internationally recognised specification for carbon neutrality), the global standard for zero carbon. The COP26 Sustainability Report contains information on the measures we took to deliver a sustainable summit, prevent and decrease greenhouse gas emissions, and identify lessons for upcoming COPs and major events (Dwivedi et al., 2022). This shows leadership and ambition of countries in sustainable event management.

The scientific community would be expected to support the work performed by policymakers. For commitment towards carbon neutrality and the methods industries or countries take to achieve and verify it are outlined in the Carbon Management Plan: PAS 2060 Qualifying Explanatory Statement (COP26, 2021). This study seeks to demonstrate efforts that have been made by companies all over the world to negotiate a deal to improve energy efficiency and reduced emissions gas (GHG) emissions (Calise et al., 2019). Various sectors like transportation, construction, and mining require non-renewable resources, which negatively impact the environment and pose significant challenges for countries like economic crises and social concern (Abdella et al., 2020). World forums of SD use various indicators, competitive indexes, and rankings to measure and track SD goals at the macro level. However, the accountability of stakeholders and law makers is still finite because of the absence of proper detective models (Pérez-Ortiz et al., 2014).

Environmental sustainability is so extensive and includes many

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trade-offs that challenges are sometimes explained away with overly simplistic, "sufficient," and self-interested solutions. The environment can be impacted by trade in both positive and negative ways. As we can see, increased pollution and the degradation of natural resources have a direct influence on the environment with economic expansion. Here, AI is crucial in tackling problems with environmental sustainability. AI can have significant implications for trade in various sectors of our environment (Nishant et al., 2020). For example, we can see a trade of digital assets or intangible assets in the form of tokens, which can be improved by the use of blockchain technologies by maintaining regulatory compliance, increasing the speed of transactions, and digital tokens for speedy transactions, which eventually affects global trade environment (Pournader et al., 2020). Similarly, we can see a trade-off between the total cost of production and environmental influence, initial investments and long-term benefits to the environment, and a trade-off between total cost and CO2 emission (Wang et al., 2011).

In general, we can say that organizations are joining hands to bring trade-offs between various factors that are important for development and environmental sustainability practices. Environment trade-off decisions propose a multi-objective optimization model that helps understand emerging trade-offs among various constraints of projects and environmental feasibility (cost, time, and quality) (Wang et al., 2011). Researchers proposed using Artificial Intelligence (AI) can improve the environmental sustainability of products and services (Frank, 2021; Dwivedi et al., 2022).

AI plays a crucial role in a nation's economic growth and has the potential to reach up to $15.7 trillion global economies by 2030 (pwc, 2018). AI can be explained as an assemblage of many technologies (Tredinnick, 2017) and methods, that is, analytical and emblematic (Hoehndorf and Queralt-Rosinach, 2017). AI aim at expressing human reflective functions (Jiang et al., 2017) or demonstrating dimensions of human intelligence by executing several tasks/decision making (Kushwaha et al., 2022), mostly measuring analytical, analytical intuitive and empathetic intelligence. AI is still facing many challenges in various areas. For example relationship between the continuous environment states and optimal control decisions (Qi et al., 2019), techniques for predicting crashes (Abdel-aty & Haleem, 2011), timely detection of hazardous traffic condition formation (Hossain and Muromachi, 2012), short-term crash risk results could disclose the crash hotspots and city planning (Bao et al., 2019), large-scale entrepreneurship development projects (Elia et al., 2020), malware detection (Mohaisen et al., 2015), accurate wind power forecasting and prediction (Marvuglia and Messineo, 2012) and more. However, the presence of AI is very restrictive and concise to specific areas of the environment and operations. For example, cryptocurrencies need as much energy as required to sustain Finland (Cambridge Centre for Alternative Finance, 2020). So, we need to explore AI's impact on sustainability which plays a crucial role in addressing the socioeconomic behavioral challenges associated with economies.

Increasing demand for AI for sustainability increases the data volume and, consequently, energy requirements of infrastructure increase in the future. So, it requires approaches for storing, analyzing, and visualizing data for incorporating AI in a study of sustainable development. However, it is debatable whether AI is a key or a part of the environmental sustainability issues (Kopka and &Grashof, 2022). Researchers indicated the economic effects of AI surrounding resource consumption; however, questions related to sustainability and effect of AI on sustainability remain unanswered (Khakurel et al., 2018). Many researchers have performed the literature review by extracting a single dimension of sustainability and highlighting the various challenges of that sector (Ansari and Kant, 2017). In this paper, we tried to highlight the range of methods, challenges, and barriers associated with adopting AI for sustainable development. We aspire to find answers to the following research objectives to provide valuable observations:

1. To investigate the range of methods used in AI and sustainability
2. To better understand the issues, opportunities, and barriers deemed significant for SD while using AI.
3. To establish how AI impacts SD and the nature of such impact.

The literature review section has been divided into two steps. Firstly, we highlight the systematic literature review of 287 research papers where the focus was on the kind of barriers and methodology employed to address that barrier. We also highlight the various domain of the environment where AI has been employed, like supply chain and healthcare. Secondly, we present findings related to various AI-infused methodologies employed in various environment segments. Further, this study has contributed to literature at two levels. First, our literature review will employ PRISMA-based literature to map the various antecedents and future challenges of AI in sustainability. Second, it finds various future research directions for academic researchers. This literature highlights the various methods used to improve sustainable practices at a small to large scale using AI. The rest of the study will be surrounded by finding answers to the above-stated questions.

Further, the paper's organization in the given paper will be like this: Section 2 presents the literature review on AI and sustainability and its impact on the environment. Section 3 elaborates on the research method used for this study. Section 4 outlines the findings of the study explaining the methodologies employed in this domain and its descriptive analysis. We present the discussion and implications, followed by limitations and future research scope. And lastly, the conclusion in Section 6.

2. Background literature

The key step in developing SLR is understanding the study's scope and surrounding parameters associated with the research objective. Clearly defining the review's scope and boundary helps define the embodiment and elimination criteria. We present the definition of key terms associated with the identified domain in Table 1.

2.1. Evolution of AI

AI has developed over the last several years into a potent tool that enables machines to think and behave like humans. To do its function, AI possesses intelligence, learning, and reasoning abilities. *Intelligence* in AI is an ability to do *reasoning*, problem solving, *learning,* and integrate various human functions like perception, attention, memory, language, or planning. Reasoning in AI helps machines think rationally and apply deductive, inductive, abductive, and monotonic approaches to available sets of data, facts, and knowledge to make constructive predictions and valid conclusions (Bittencourt et al., 2009). Another aspect of AI is learning, which improvises the knowledge of an AI program and is classified into supervised, semi supervised, unsupervised, and reinforcement learning. Learning is an important part of artificial intelligence, yet it will not guarantee that the statistical rules, which machine has learnt will be able to adapt to rapidly changing environment. Hence, adopting an AI-based method that will unlearn, adopt and change as per need is important for SD practices (Bhatt and Zaveri, 2002). Supervised learning is the data mining task of inferring a function or class from labeled training data. In semi-supervised learning, we make use of typically a small amount of labeled data with a large amount of unlabeled data. In unsupervised learning, we find hidden structures and patterns in unlabeled data. Reinforcement learning models are also gaining popularity where machines learn through trial-and-error methods, galvanizing how we humans do some tasks and proceed based on positive or negative rewards as an outcome (Singh et al., 2022).

Another major fundamental block of AI is adaptation, where machines learn through movement, taking cues from sensation, controlling the environment, and developing situational awareness. AI tries to learn and adapt like biological organisms and uses mathematical functions to mimic real intelligence, as demonstrated by living organisms and

Table 1
Definition of key terms.

Reference	Description
Artificial intelligence	
Suman (2021)	"Artificial intelligence-the mimicking of human cognition by computers-has come a long way since being an imagination in science fiction to becoming a reality in ubiquitous sense of modern technology."
Bittencourt et al. (2009)	"Artificial intelligence techniques to provide personalized interactions, aiming to improve the learning and problem-solving processes."
Kotsiantis et al. (2007)	"Machine learning, an artificial/computational intelligence technique, uses a set of attributes and searches for correlations between the attributes and performance of the learning algorithms."
Chai et al. (2021)	"Emerging big data and Artificial Intelligence (AI) technologies show significant advantages and efficiency for knowledge sharing among intelligent vehicles."
(Kopka and &Grashof, 2022)	"One of the newer trends of this digitalization process is the so-called artificial intelligence (AI), which is often seen as a panacea for all kinds of problems."
(Acemoglu and Pascual, 2018)	"The proficiency of a machine to emulate intelligent human behavior" or "an agent's potential to achieve goals in a broad environment
Sustainability	
(Shinde et al., 2022)	"To achieve sustainability goals holistically, housing cooperatives need to make active efforts to bring their tenants on board while collaborating with them and spreading awareness about their potential rebound impacts and the possibilities of reducing them."
Karakutuk et al. (2021)	"The goal of sustainability is to optimize the resources according to human needs while considering the Economic, Social and Environmental pillars."
Casazza & Gioppo (2020)	"The focus on social sustainability of robotization and AI constituted a novelty concerning previous works, which only investigated the technological application of robots to the theatre, instead, then considering the messages to be shared with the public."
Gonzalez-Feliu & Morana (2014)	"The notion of sustainability varies for each stakeholder due to the significance they give to the three components (Economic, environmental, and social) of sustainability is different. "
Kontokosta &Tull (2017)	"Cities are increasingly adopting long-term sustainability plans designed to increase the efficiency of energy infrastructure, reduce operating costs, and mitigate the adverse effects of climate change."
Environment	
Wang et al. (2020)	"A network environment is defined as a particular time and site where we collect our network traffic to train or test our classifier."

animals using individual and sometimes a combination of algorithms (Kar, 2016). Literature indicates a significant advancement in AI by modifying existing methodologies. Conventional approaches like ANN and decision trees are ineffective at adapting to different settings. Recent models like reinforcement learning, Convoluted Neural Networks (CNN), Federated Model, TinyML and Deep Neural Networks (DNN) can handle challenging problems coupled with the use of AI in sustainability (Singh et al., 2022). In this study, we considered summarizing the methods of AI used to study sustainability related challenges.

2.2. Sustainability and environment

In many countries, population rates, geographical factors, infrastructure, health conditions, and infrastructure also challenge sustainable development practices (Kuenzel et al., 2016). Additionally, these nations face financial obstacles while implementing sustainable management techniques (Sarkis and Dou, 2017). Therefore, we require a thorough review that can help researchers in performing studies carried out in this field and what further can be done to lessen the difficulties and barriers related to AI in sustainable development.

The term "sustainability" has been used in a variety of contexts and is used in several industrial sectors, including those that produce palm oil (Farhana et al., 2018), manufacture products (Aziz et al., 2021; Zangaro et al., 2021), manage forests (Oliveira and Luís, 2020), and engage in fishing (Oliveira and Luís, 2020). Environment sustainability implies interacting with the environment to manage the naturally available resources and not imperil the future of coming generations by exploiting all the available resources (Zarte et al., 2019).

A plethora of environmental policies are intended to improve resource capacity and efficiency while limiting the use of harmful offerings that can have an adverse impact on the environment. This can aid in cost management but will lead to high impact consumption (rebound effects) (Shinde et al., 2022). The studies performed in economics can help researchers estimate the overall rebound effects on countries' economies, but they have not necessarily considered the environmental assessment (Shinde et al., 2022). We can witness the effects of the environment on numerous facets of global economics. A number of institutions and organizations are integrating sustainability into their daily work to address environmental problems. For instance, Froemelt and Wiedmann (2020) emphasized the importance of households in addressing global emissions and the necessity of changing consumer resource consumption patterns to lessen overall adverse environmental effects. Artificial intelligence (AI) based techniques can help reduce emissions in a variety of ways, like as facilitating the development of low-carbon technologies, improving sales forecasts, limiting system waste, satellite imagery, improving energy efficiency, predicting vehicle emissions from smartphone GPS traces, boosting single buildings, highlighting behavioral patterns, and planning and running low-carbon infrastructure (Dwivedi et al., 2022).

Policies and regulations are other parameters illuminating the government's role in managing various sectors like the food sector for adopting technologies like AI and blockchain (Hasibuan and &Dantes, 2012). Companies are using various decision support system frameworks to help organizations collaboratively handle economic, environmental, and social impacts in their supply chain. However, multi-criteria integrative approaches are needed to mutually optimize the economic, environmental, and social costs (Allaoui et al., 2019). For example, the concept of sustainable or green products has converged and has rapidly changed from being viewed as a constraint to being considered a means of substantially maximizing output (Sarkis and Dou, 2017).

2.3. AI in sustainable development

AI has the power to hasten global endeavors to preserve the environment and conserve resources by finding various factors like energy emission and reductions, CO2 sinking, greener transportation networks, surveil deforestation, forecasting weather, crash prediction, and efficient supply chain management (Cardil et al., 2019; Song et al., 2020). Vinuesa et al. (2020) discussed how AI could either allow or inhibit the delivery of some of the 17 goals and 169 targets acknowledged in the 2030 agenda for sustainable development.

AI in sustainable development is affecting various dimensions of different sectors. For example, AI is affecting global energy sectors, environmental outcomes, productivity, and other factors of society. There has been an uptick in the number of works being done in the field of AI, integrating AI into many facets of sustainability and solving such issues practically (Goralski and Tan, 2020; Khakurel et al., 2018). We have observed a rapid development in AI in fields like mechanics, parallelization of processors, sensors, algorithms, and software, which is enabling growth in a wide range of AI applications and is capable of scanning environments, exchanging knowledge, monitoring, and developing adaptive goals (Berente et al., 2021). In manufacturing industries, AI offers in-depth monitoring and control and gives a comprehensive view of the equipment's performance and health (Burström et al., 2021).

Estupiñán and Alvarez (2016) explained the obstacles surrounding SD and has provided large data sets on sustainability which can be studied extensively to solve the problems surrounding SD (Sachs, 2015).

AI and sustainability have been popularly summarized in four main areas: Human, Social, Economic, and Environmental. By analyzing the economic, social, and environmental information, AI can help provide quantitative analysis of various policies' effects across various sectors and make predictions about these areas. As per various studies published in Nature, AI can help achieve the 79% of SDGs (Vinuesa et al., 2020).

After numerous studies on the impact of AI on sustainability helped, many firms infuse AI into developing their products to improve their SD practices (Frank, 2021). Due to their significant impact on a variety of economic factors like project cost, business profitability, a variety of environmental factors like CO2 emissions and NOx levels, and health and safety, the active management of tools and equipment in construction projects (like accelerometers) is a crucial job for many builders and specialized earthquake contractors (Kassem et al., 2021). Government organizations are also developing various strategies to address the concerns of circumambient sustainable development issues (Hummels and Argyrou, 2021). For example, AI-enabled medical drone applications in one country's healthcare sector can significantly impact other countries' healthcare sectors and help attain sustainable development goals with stress on climate (SDGs 3,8 & 13) (Sakyi et al., 2021). Also, we can provide sound health, unsoiled water & sanitation, affordable and clean energy, sustainable economic practices, consumption pattern, biological life, innovation and infrastructure, and climate change by practicing simple SDGs practices like reducing carbon emissions, using noise free drones for the delivery of products and services (Sakyi et al., 2021).

AI with the ability to handle a large data set can be proved highly effective in the innovation sector. The AI-based software predicts future consumer purchasing trends and can eventually reduce inventory management overhead costs, offer reasonable storage and low-cost rent, and increase tenants' income (Shinde et al., 2022). For instance, nations that engage in supply chain management utilize both physical and digital chain networks, high volumes of work, efficient resource allocation, fulfilling deadlines employing AI technologies in optimization, and network coordination among diverse service partners (Toorajipour et al., 2021).

3. Research methodology

3.1. Systematic literature review

Systematic review is widely used in physical and medical sciences and now has been making progress within computer science to analyze the wide range of data that is spread over the internet to reach "quantifiable, reproducible, systematic, clearly stated, and extensive coverage" of a specific topic (Weed, 2006). We have used a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology for our systematic literature review due to its comprehensive reviewing method. The PRISMA approach provides a detailed checklist of all the parameters to carry out a reproducible review by other researchers and will generate accurate data for future research (Booth et al., 2020). The PRISMA method consists of many steps that can be relevant for carrying out the research in medical and physical science, yet it is in the exploring phase and is now being adapted for computer science research. The PRISMA-based approach for systematic literature review helps to ensure the quality of the review, allows readers to analyze strengths and weaknesses, permits cloning of review methods, structure, and format of the review using PRISMA, and provides a reference point for others in the field.

We used Scopus database for searching the articles for this systematic review as it provides a more extensive range of scholarly information to get a more profound idea about the research we want to perform. Research papers indexed in Scopus have been included in the database after rigorous selection measures, which mean we can rely on them for academic research (Kumar et al., 2022; Tiwary et al., 2021). To perform our research, we used a set of keywords together with a search in the database within article titles and keywords. To extract the literature related to "AI" and "sustainability," the words 'AI,' 'artificial intelligence', and 'machine learning' were searched together with using Boolean logic (AND/NOT) 'sustainability,' and 'environment'. Using such terms, it generated some limitations: generic articles related to 'neural network,' 'cognitive,' 'sustainable development, 'sustainability,' 'sustainably,' or 'sustainable' may have been missed. Yet, these limitations generated 7753 articles in 'Article and Review', which seemed comparable to similar reviews in this field. All of these papers were then manually reviewed as part of the screening procedure to make sure they were pertinent to the subject, and articles that weren't were excluded. We have not taken conference paper, books, and conference review for this literature review. We did content analysis methodology for the identification of the themes to ensure the reliability among the themes. We undertook intercoder reliability test among specific themes before reporting in section 3.1. We searched the keywords on Scopus individually and numerically measured the agreement between the data that came out of it. Titles and keywords of relevant database were screened by two times to validate the search result. Full-text articles were then screened for relevance, and duplicates were removed. Fig. 1 represents a flowchart opted for search papers.

Our research yielded a total of 287 publications from 24 journals that belongs to A and A* journal (ABDC listing) and 2 and above ranked journals (ABS listing). The quality criteria for journals were kept ensuring articles included have undergone rigorous peer review before publication. We read and analyzed the ideas surrounding our key objectives present in the paper through iteratively reading the introduction, methodology, discussion, and critical findings. After collecting the relevant articles, articles were then coded according to various categories. Further, we present a systematic review of key ideas, themes, and contributions that emerge through the regressive study of this literature review paper.

3.2. Results

In this section, we unveiled the descriptive results related to year of publications, industries, methodology, use cases, and the content analysis resulting in finding out types of learning, barriers, and opportunities in SD while using AI.

3.2.1. Distribution of publication

The year-wise publication of research studies was analyzed for this systematic review in Fig. 2. The Figure highlights the number of researches surrounding AI and its influence on sustainable development increases with time. There is an increasing growth of focus on publishing articles on AI-induced sustainability.

Further, we explored what kind of AI learning researchers prefer to perform the study. We analyzed the learning algorithms adopted, which subsequently can help determine which type of learning is more frequently used by researchers for the study. We found that most of the research surrounds supervised learning. Of all the papers used in this study, 52%are based on supervised learning. Also, for 22% of studies, researchers have used an unsupervised learning approach. However, we can see that the least preferred algorithm employed by researchers is reinforcement learning which is yet to be explored.

Further, we identified that the dominant AI algorithms used by authors in studying sustainability are regression, Decision Support System (DSS), Random Forest, Artificial Neural Network (ANN), and Convolutional Neural Network (CNN) to study the environmental overall impact (see Fig. 3). These algorithms help improve the areas focused on sustainable data sources, power supplies, and infrastructure to reduce and measure the carbon footprint using training and tuning algorithms. Among all the algorithms, 54% of our total final numbers of articles have used a regression-based approach to establish the relationship between AI and its implication for sustainability. Further, 45% of articles are surrounded using reinforcement learning, which can perceive and

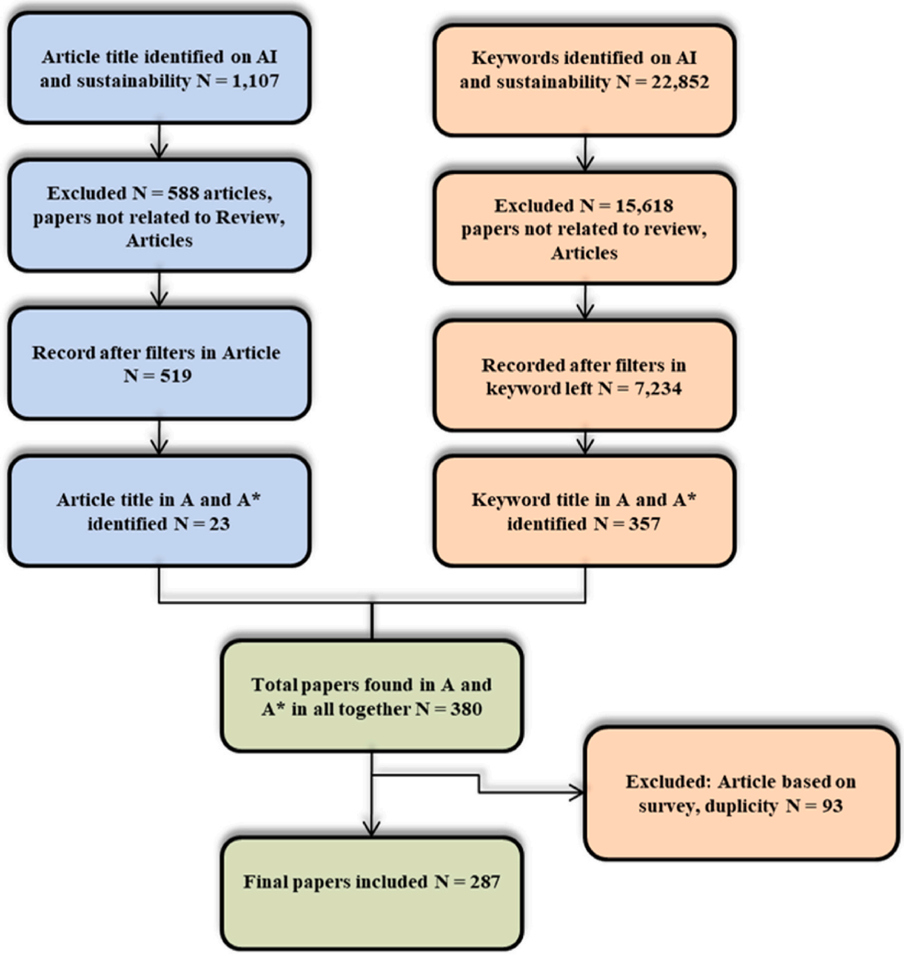

Fig. 1. Process used to select the articles for this study.

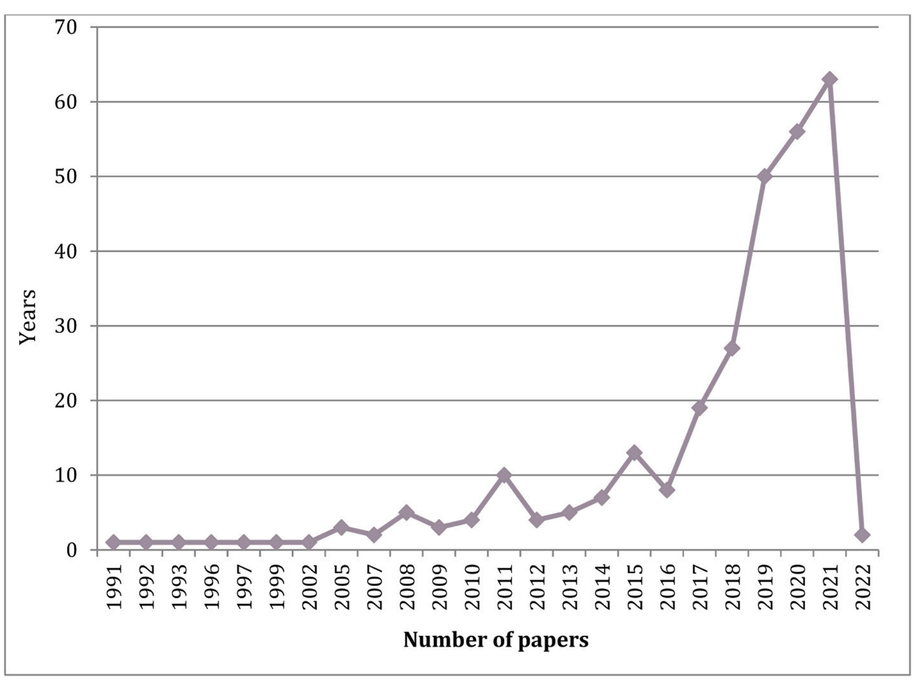

Fig. 2. Number of publications per year.

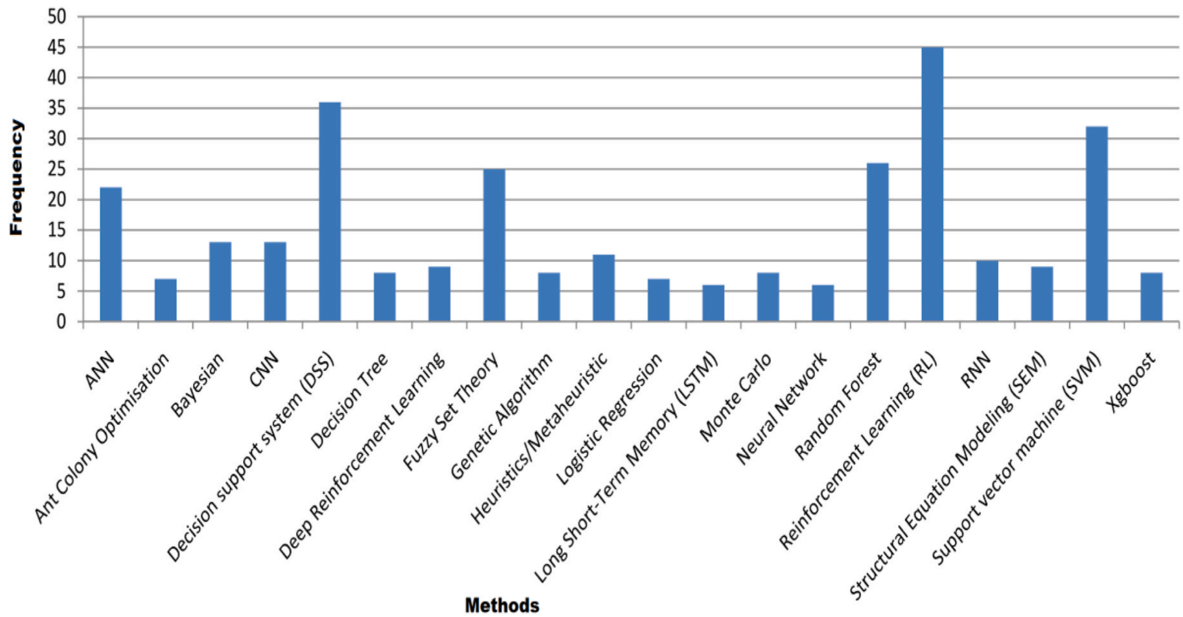

Fig. 3. Methodology used in selected papers.

interpret its environment through trial-and-error method. Also, 36% of articles have used the DSS to support the determinants, for making judgments and courses of action in an organization to analyze the massive amount of data, compiling comprehensive information available from the surrounding environments to solve the problems and take intelligent decision. Rest, 32% of articles have used Support Vector Machine (SVM) based approach. There are other algorithms like random forest, Fuzzy Set Theory, ANN, CNN, Bayesian, Deep Learning, Structural Equation Modelling (SEM), Deep Reinforcement Learning (DRL), Xgboost, Decision Tree, Monte Carlo, Adaptive Learning and more. However, algorithms like path model, loop routing, empirical analysis, perceptron model, topic modeling, game theory, genetic algorithm, swarm optimization, and more are less frequently used methodologies. We present all the methodologies used by AI and sustainability related articles in Appendix A.

Also, we tried to plot a graph on various industrial sectors (division-based on SIP index) where AI-based models were employed to improve sustainability. From Fig. 4, Transportation/Communication/Electric/Gas/Sanitary Services is employing artificial intelligence higher than any other sector. Also, 34% of the time, AI is being used in non-classifiable sectors like society, IT, environmental issues, food sector to improvise these sectors using various AI and machine learning models. Also, it is very clear from the above plot those mining and wholesale trade sectors are still have not incorporated AI in their practice.

The systematic literature review included 287 papers from 21 different journals (Fig. 5). The comprehensive array of journals shows the multi-disciplinary nature of AI in sustainability like it has included technology, energy, transportation, healthcare, security, management, finance, operations, academic and more.

It is apparent from Fig. 5, that Journal of Cleaner Production has the highest number of articles published in the interface of AI and sustainability followed by Accident Analysis and Prevention.

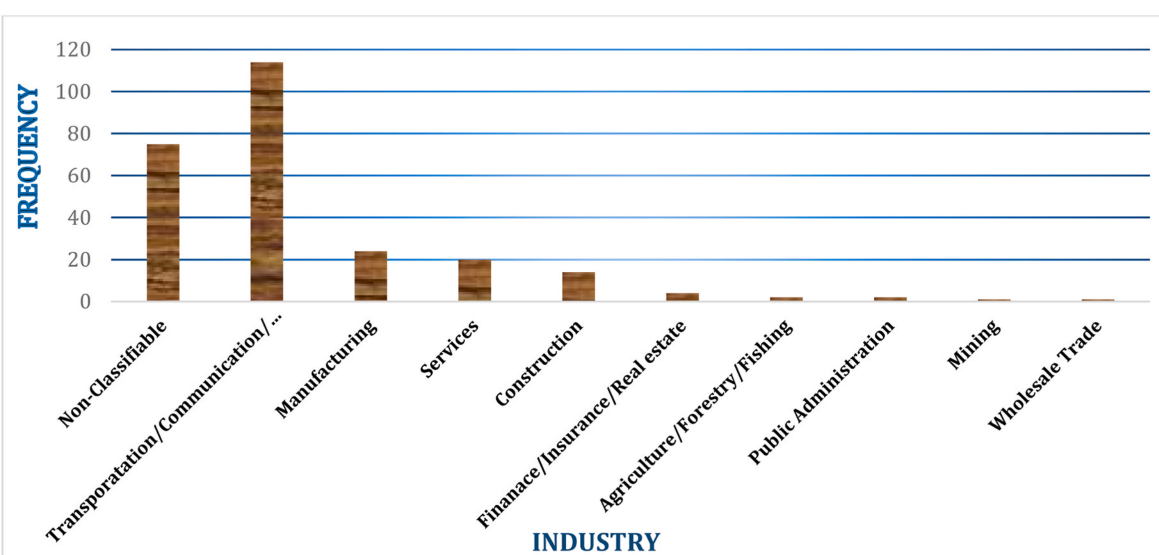

Fig. 4. Industry classification based on SIP.

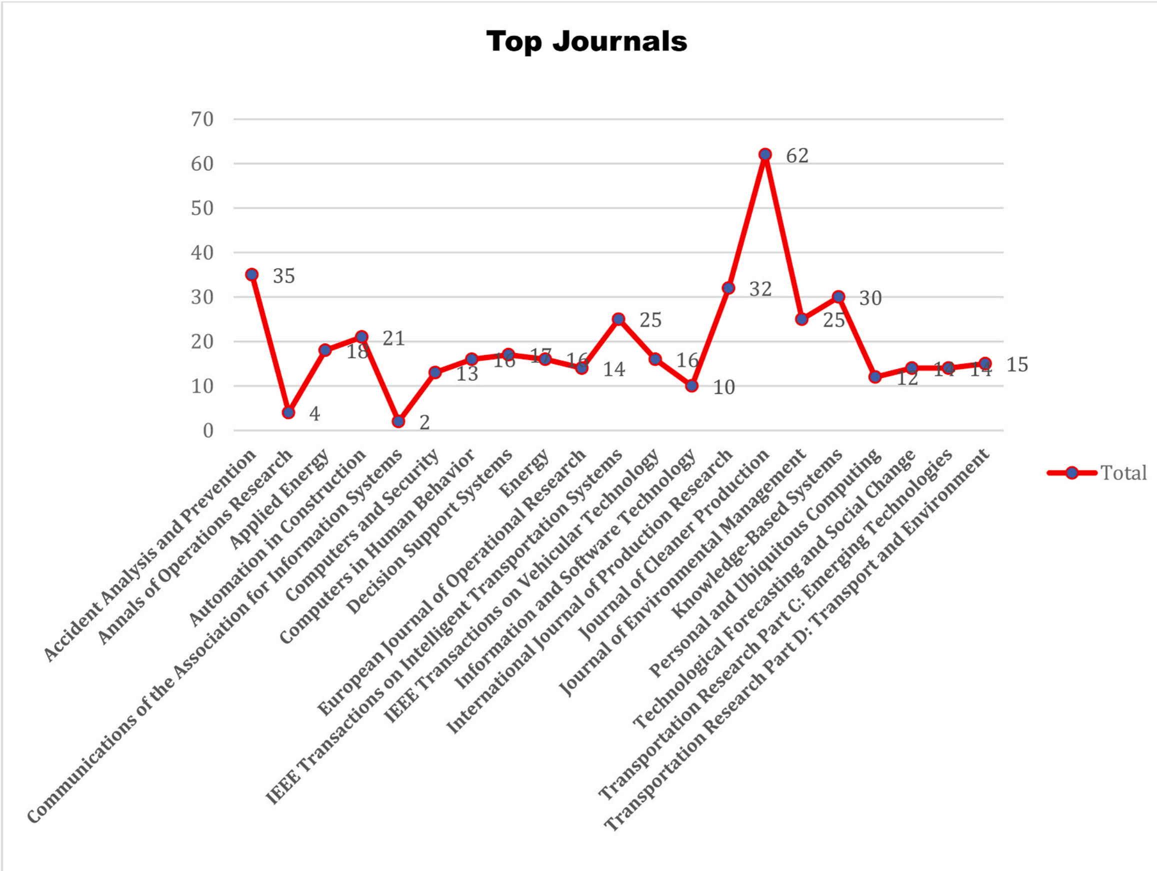

Fig. 5. Preferred journals for AI and Sustainability.

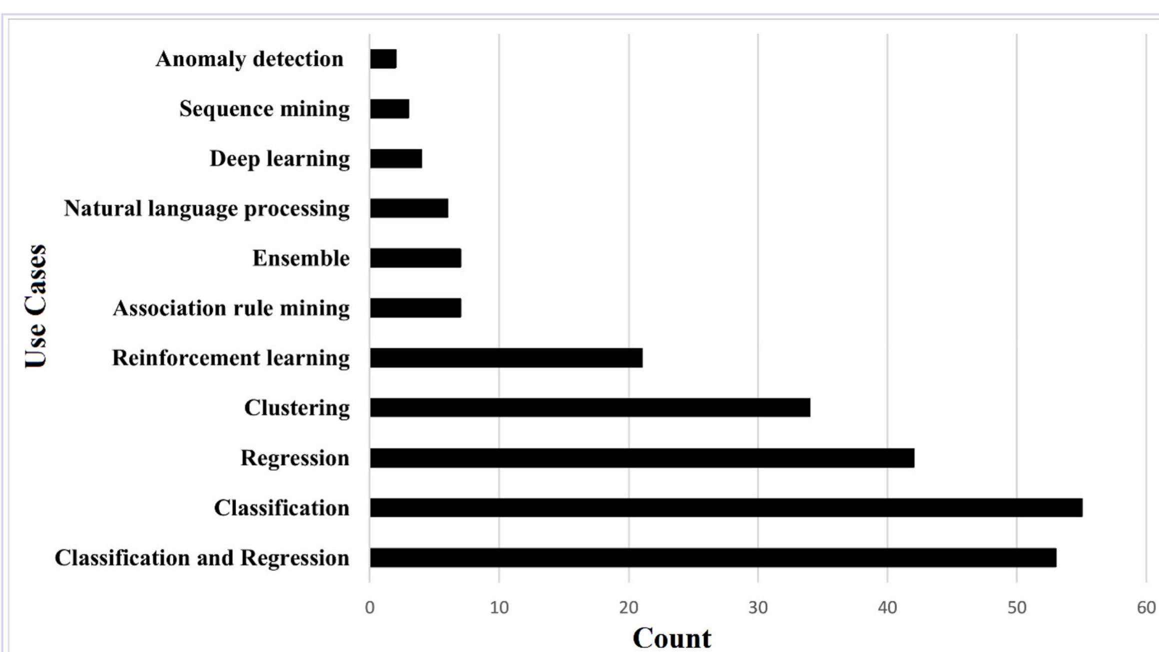

Fig. 6. Usage of AI algorithms in sustainability.

4. Findings

4.1. Range of algorithms used in AI and sustainability

Descriptive analysis: As per the bibliographic portfolio, it was observed that 3.4% of article and review papers are available for our research focused on artificial intelligence-induced sustainable development practices. The famous algorithms and methods used to study this area are RL, DSS, ANN, SVM, regression, and fuzzy set theory.

Also, we plotted a graph to find which type of use cases are used in papers. In Fig. 6, we can see that researchers have used classification maximum time as a used case to predict the result based on available data. The next most likely used case is classification and regression. Researchers are also incorporating RL in research; however, it is still in nascent. Other use cases like association rule mining, ensemble, NLP, DNN, sequence mining, and anomaly detection are still emerging.

4.2. Issues, opportunities, and barriers significant for SD while using AI

We need the support of necessary regulatory insights into AI-based technologies to enable sustainable development for the growing implication of AI. Failure in doing so could result in various issues like loss of transparency in information sharing, safety issues, and other ethical challenges.

Issues: Though we are moving toward sustainable development, there are still many challenges and issues associated with the future integration of AI in sustainable development. For example, there have been enormous socioeconomic impacts on the growth of AI; the palpability of these services is still in the virtual phase and is facing many challenges in its implementation (Kopka and &Grashof, 2022). Although there is a harmony about the enormous socioeconomic impacts of AI's ongoing and future developments, the tangible mode of this advancement is still highly discussed (Obschonk and Audretsch, 2019; Zhang and Dafoe, 2019). Based on the content analysis of the 287 articles, we have grouped barriers into the following segments: (i) Environmental, (ii) Social, and (iii) technological (see Table 2).

Opportunities in this area: AI can help organizations and society in many ways. Organizations can use AI for utilizing subsist assets more effectively, assign resources more effectively and enhance how data and facts are supervise and shared across the various dimensions. In the financial sector, AI can bring smart chatbots for customer services (Kushwaha et al., 2021), personalizing services for individuals, and customized customer care services. Using AI, we can determine forthcoming power outrages by accurately forecasting weather patterns and promptly estimating the power grid for weak spots. This assessment can help reduce catastrophes that can harm the environment because it allows users to prevent outages and respond quickly whenever such issues occur.

4.3. Establishing how AI impacts SD and the nature of such impact

Goralski and Tan (2020) states that AI significantly impacts business

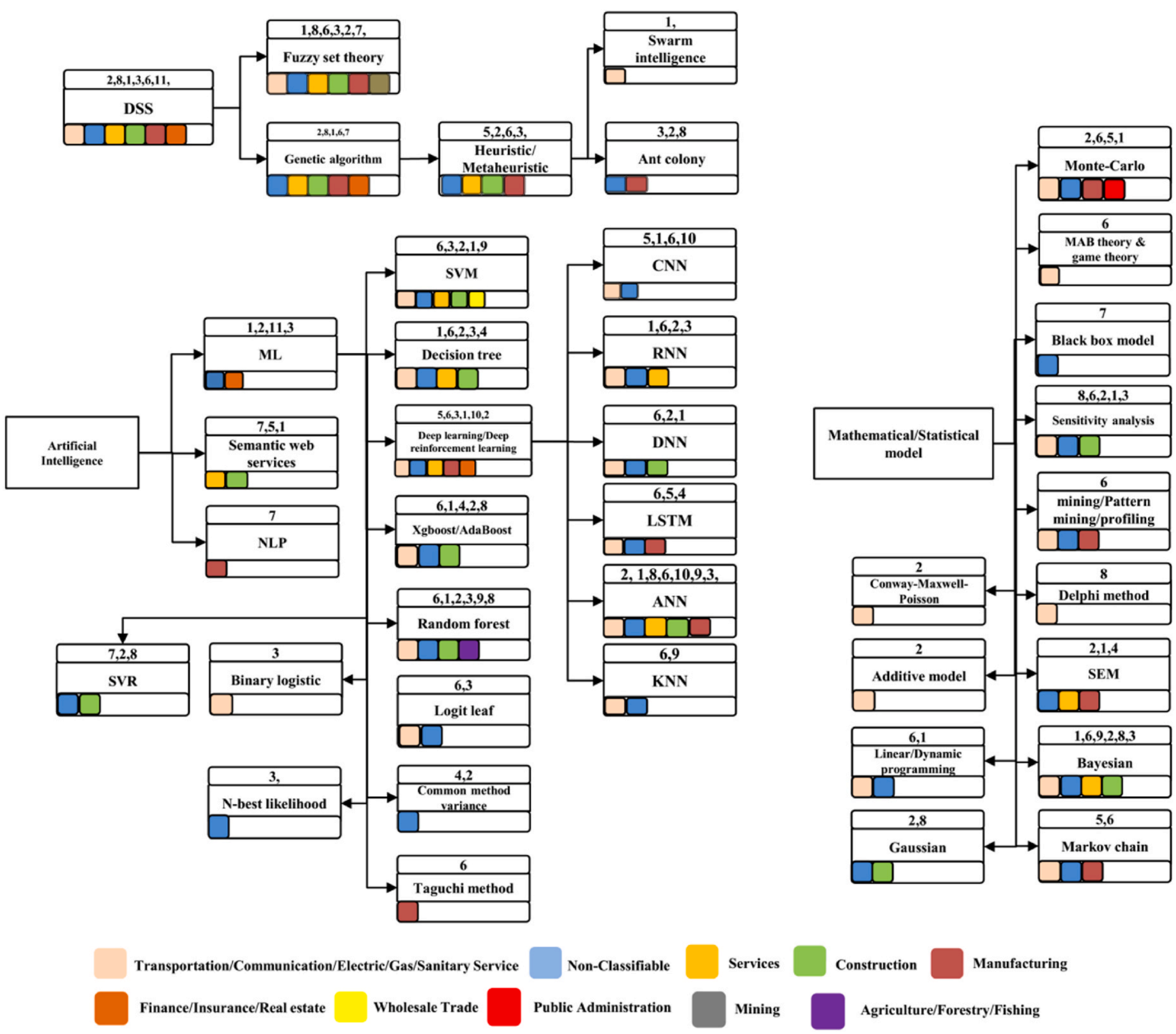

Fig. 7. Pictorial representation of industries using various methodologies.

Table 2
Summary of barriers and their description from the selected paper.

Groups	Barriers	Description
Environment	**1.** Meteorological conditions, unknown background conditions, worker quality and demand, and site logistics (e.g., traffic, emissions regulations). **2.** Poor management, security, stack, network, cost, software, hardware. **3.** Technology, security, knowledge sharing, user compliance, cost saving, machine morals for artificial intelligence technologies, and paucity of legislation/ regulation. **4.** Construction, household behavior, consumption pattern, solar and wind energy, congestion, pollution, global warming, and noise. **5.** Efficiency measure, environmental pressure, energy-intensive manufacturing, Waste management, dumping.	**1.** Live streaming of proper data for production management is important for works which possesses uncertainties like rework, failure of machines and tools, lack of resources, and catastrophe that leads to delay and over-budget delivery of products (Zohoori et al., 2019). Policymakers are required to incorporate environmental indicators in the designing phase. **2.** New technologies in agriculture for improving efficiency may create challenges like security, stacking, inter-operability, networking, cost management, software, and hardware maintenance (Maroli et al., 2021). **3.** Blockchains are widely used for security issues during information sharing process (Chai et al., 2021a). Public stakeholders (e.g., the authorities) may be concerned of environmental issues like traffic congestion, soiling, global warming, and noise without distorting urban development planning and providing employment (Kuutti et al., 2019). **4.** Keeping things like stream connectivity abreast that overlook unmapped dams, help in proper cognizant of emergent anthropogenic activities like culverts (Buchanan et al., 2022). **5.** Environmental problems linked with rebound-based levy related to the respective emission factor, i.e., emission per expense in any consumption category are essential for determining the environmental impact (Shinde et al., 2022; Stevovic et al., 2021). Energy consumption pattern not only reduces the fuel bills but also decrease the negative environmental impacts (Do et al., 2014).
Social impact	**1.** High-end technology needed for interaction between digital content and physical environment, quantifying resource efficiency, energy-saving, real-time location tracking, cyber-attacks, strategy, IoT enabled product, unstructured data. **2.** Knowledge presentation and inference, planning, identifying, learning, uncertainty in knowledge processing, and dialogue proceeding.	**1.** The supply chain management workers can exploit digital twins on society, environment, and technology that directly or indirectly affect supply chain management (Kamble et al., 2022b). **2.** AI in education is about systems that include problems associated with AI in area, like knowledge management and reasoning, planning, prognosis, training, uncertainty in knowledge, and chatter processing (Bittencourt et al., 2009).
Economic impact	**1.** Greater data transparency, data accessibility, consumption, and policy implementations, forecasting of energy consumption pattern. **2.** Data availability, time management, accessibility and reliability issues, management issues. **3.** Designing and operation management, quantifying benefits	**1.** Service companies have important data resources from utility distributor to help cities planner to evaluate sustainability and carbon reduction methods in the cities. Such method of data consumption pattern and policy impacts, sanction for improved forecasting energy demand and a more basic understanding of urban energy kinesis (Kontokosta &Tull, 2017). **2.** Acceptance and maintenance are emerging issues that stakeholders must manage. Issues in performance are another area that requires monitoring. However, to enhance acceptance, utilization, and maintenance a proper response mechanism needs to be assimilated in the system where GPS (Global Positioning System) can enter comments or guidance for improvement that are regularly examined and cater into future outline cycles. Further, utilization needs to be vitalized and monitored (Zhuang et al., 2013).

and society. The intelligence of machines by incorporating deep learning has capabilities to either disrupt or enable effects on business, governments, and society. In this paper, we outline the needs of society with artificial intelligence to study the various impression of AI on sustainable development with a precise focus on the advancement of SDGs.

4.3.1. *Impact of AI on the environment*

4.3.1.1. AI in water management. There has been an enormous demand surrounding sustainable solutions for treatment, transportation, and water recycling. With increased pollution and fresh and clean water reduction, we need technology for its sustainability. Water management is one of the 17 SDGs of the world. All the particulates matter present inside the water has varying toxicity levels and needs an appropriate measure to reduce their impact on the environment and society. AI and machine learning can be effective measures for treating and detecting harmful particulates in the water.

The algorithms and approaches used for the treatment of waste water can have more significant implications on the life of humankind. AI-driven software computational framework is needed to find the various alternatives for managing wastewater. AI can constantly adapt to new sources of information. By incorporating the new service algorithms of AI, a new strategic model can be created to improve wastewater management and its productivity. The knowledge of AI unties the power of water professionals (Hill, 2018).

However, there is an issue with the AI in water management in the kind of data transferred to it and the management's level of understanding of those data. Human skill has a limitation in understanding the machine language and incorporating those understanding in finding the solutions to the problems. For now, we still need experts to understand AI, but with the advancement in time may be human interventions will not be required anymore. The goal of AI is not to be exemplary but to help manage the resources more efficiently.

4.3.1.2. AI and agriculture. With this birth rate around the globe, the world's population will reach 9.1 billion by 2050, and food requirements will boom to 56% from 35% (Alexandratos and Bruinsma, 2012). Hence, we will not only need a mechanism to boost production but also to monitor diseases and perform predictions. Earlier soil quality and crop health were monitored manually and through human observation. However, new algorithms are more appropriate and accurate. We use drones to capture aerial images and train our model accordingly to analyze data properly. For example, visual sensing AI can analyze and interpret these data to capture crop health, make accurate yield predictions, track crop diseases, and do climate analysis for crop growth.

The database for AI starts with identifying the 30 most important diseases that can affect crops and are seemed significant for the AI training model, and the model can identify almost 99% of images that need to be of good quality, but this efficiency reduces to 32% if image quality is deficient (Goralski and Tan, 2020). However, prediction solely based on image analysis is helpful on a small scale, but a more comprehensive system is needed based on more than just an image on a large scale. However, the new model based on AI uses even low-quality data to make the analysis; hence, even small farmers can use this application to improve their agricultural output. So, farmers of low-income countries who lack resources can use AI to improve their agricultural products. AI can help mend the gap between developed nations and developing nations.

4.3.2. AI and transportation

AI plays a crucial function in the sector innovation of autonomous vehicles (AVs), one of the breakthroughs in transportation. An autonomous vehicle needs an accurate analysis of its environment to work efficiently (Arnold et al., 2019). Internet of the vehicle is a distributed network expressed by collaborative learning through data sensing, computing, and operating. The growing high amount of data and artificial intelligence can be seen as an advancement in knowledge sharing among intelligent vehicles (Chai et al., 2021b). Even after a large set of data is available for analysis, knowledge sharing faces various critical challenges. The existing vehicular system lacks security and faces reliability challenges in the data sharing process. Malignant vehicles can severally impact the knowledge sharing process by sending wrong signals, fake information, or interfering with received knowledge. This may cause a severe threat to privacy when all the information is aggregated at the central server to process the global training model as the internet of vehicles includes information such as personal information of users like location preferences, driving patterns, which is indirectly related to users' safety and driving condition (Chai et al., 2021b).

Hence several challenges need to be overcome before commercializing the use of autonomous vehicles for widespread use. This section will discuss the various impacts and technological objection that DL based autonomous vehicles possess. It is essential to acknowledge that other than technological challenges, other issues like user acceptance, cost efficiency, machine ethics for AI, and the absence of legislation/regulation for autonomous vehicles need to be accosted (Kuutti et al., 2019). Wang et al. (2021) has built the model called ADLCM by incorporating various decision thresholds to throw light on various impact factors of driving environments on driving decision. The study by Hossain and Muromachi (2012) has introduced another factor called 'congestion index' (CI) using the combined effect of speed and flow at each detector position. There are other types of issues in traffic management, like traffic encryption issues. Various machine learning algorithms are employed, like analyzing statistical flow features (Wang et al., 2020) to address the challenges surrounding autonomous vehicles. It has been seen that the danger of collision is most significant at nighttime, for any speed and traffic flow. At signalized intersections, the probability of accidents is highest. However, research still have not consider the non-signalized intersection, meteorological conditions, and road surface state as a determinant of the number of accidents at each intersection (Mussone et al., 1999).

4.3.3. AI and healthcare

The potential for AI and ML in the sector of healthcare is very vast. One of the most remarkable benefits of AI is to predict disease without human interference, with great accuracy. Technology encourages people to incorporate healthier behavior in themselves and adopt a healthy lifestyle. AI helps healthcare professionals deliver better results related to healthcare service and provide better feedback, guidance, and support to patients for staying healthy.

The prediction model of AI can help determine the environmental AQ and can be extended to predict situations that are reliable in prediction techniques (Schürholz et al., 2020). Providing an accurate and customized air quality index is essential for city collaborators in performing essential and critical tasks because of life-threatening threats to humans (Schürholz et al., 2020). A DL based model can also help monitor wireless signals to master various human forms, like absence, working, and sleeping, in realistic indoor environments (Fang et al., 2019). Another area of AI used is electrical resistivity measurement (ERM) is prone to various consequential uncertainties due to various factors (Dong et al., 2020). Like another algorithms XGBoost algorithm provides a authentic and predictable technique for harmonizing the results of ERM to forecast and assess the health of various structures like water/cement ratio, chloride permeability and settlement time (Dong et al., 2020). Widespread use of artificial intelligence in healthcare involves the primary application of NLP based approach to develop a proper understanding and classify the clinical documentation. AI helps healthcare sectors better understand the day-to-day needs and classification of people who need healthcare facilities to provide better guidance, feedback, and any support people need to remain healthy.

In the future AI in the healthcare could involve tasks that range from elementary day to day activities like answering calls to reviewing records of the patients, population health forecast and analytics, deriving the significant effects of drugs, designing healthcare tools, radiology image sensing, clinical diagnoses, and treatments and more.

4.3.4. AI and manufacturing

The manufacturing sector is the backbone of any country and has the power to influence the country's economy, environment, and society significantly. In the economy, sustainable manufacturing brings transformation and change in business model, generates the capacity for higher economic growth, makes trade services symbol of the image during the complete life cycle of production, and promotes the burgeoning of various economic modes and trade. From the environmental perspective, sustainable manufacturing brings down the consumption and wastage of raw materials, improves the effective utilization of resources, and decelerates the emission of pollution (Liu et al., 2019).

Augmented reality (AR), a part of AI, has demonstrated to be a highly conducted medium to minimize the cognizable weigh by traversing the space between work at hand and relevant information needed by availing the information to users. Augmented reality is a beneficial algorithm in the manufacturing sector where we need to perform a wide range of tasks like assembling products, the proliferation of products and processes, distributing products, and maintenance of various sections of manufacturing in the most cost-effective manner (Sahu et al., 2021). AR can be helpful in the most effective manner by reducing the overall cost associated with manufacturing and increasing production efficiency during the manufacturing various stages of product life cycle.

In the manufacturing process vast range of entities are involved like urban logistics, production enterprises, suppliers, wholesalers, retailers, logistics firms, stakeholders, and governments. Many stakeholders are also involved in manufacturing sectors like user or customers, investors or shareholders, suppliers, government agencies, and the wider section.

Governments are usually involved in making policies, planning activities, and strategy formulation of urban goods delivery to achieve sustainable manufacturing practices (Muñuzuri et al., 2005). Public stakeholders are actively involved in environmental issues concerning pollution, global warming, and noise, consequently not harming the human resource sector. Private stakeholders (like logistic service providers, manufacturing enterprises, and retailers) keep close vigilance on economic efficiency and advantages associated with the manufacturing sector because they believe that the economic condition of nations, together with fulfilling social responsibilities and environmental protection and contribute to the sustainability of urban logistics (Tian et al., 2020).

Kamble et al. (2022) highlighted that digital twin allow the owners to identify the operational collapse, ameliorate product quality and reduce interruption before any economic losses. Also, IoT, simulation algorithm, ML, AI, cloud computing, and so on are critical enablers of a digital twin. When we increase the range of digital twin algorithm in various sectors, from small entities to humans in the supply chain, it helps stakeholders and owners to make prompt decisions in the supply chain (Kamble et al., 2022). The authors want to highlight that environmental sustainability can be achieved by recovering durable products that have already reached the end of their life cycle through the circular economy concept. There have been several manufacturing advancements by incorporating terms like remanufacturing, repair, and restoration, showing increasing interest in metal additive manufacturing technology. To induce accompaniment manufacturing efficiency in the manufacturing sector, it is essential to optimize the core design (Aziz et al., 2021). To make changes in the supply chain management of the manufacturing sector while ensuring sustainability, a proper decision support framework is needed to help organizations manage economic, social, and environmental supply chains in a conducive manner. This framework helps build a multi-party collaborative approach across various networks to improve sustainability in delivering finished goods (Allaoui et al., 2019).

Energy consumption pattern is a key element of sustainability in any manufacturing industry and hence is a significant direction of study for studying the various impacts on the environment and climate change across the globe. A hidden relationship between energy consumption and various parameters is disclosed using models like sensitivity analysis and parametric analysis (Garg et al., 2015).

4.3.5. *AI and construction*

AI is used in construction to keep real-time interaction among various entities like workers, machinery, raw materials, and supervisors and provide real-time safety mechanisms, construction errors, and productivity measures. Accurate prediction of energy consumption in construction plays a crucial role in sustainability. Analyzing the energy consumption pattern at a large scale can improve the total energy efficiency. Hence energy-efficient buildings play an essential role in practicing sustainability and improving energy consumption pattern of society. As per Gao et al. (2021), the energy consumption model associated with different building sectors requires different amounts of energy for consumption. For example, distributed energy sectors or combined energy systems helps in identifying the variables that affect the characteristics associated with building that play an important role in designing and operating such a system. Also, the physical model designed using well-designed software like Energy Plus highlights the factors like what impacts residents of the building can have on an electric light, water heaters, and water cooler; meteorological information also impacts consumption of heat energy more (Crawley et al., 2001).

The various materials used in constructions like concrete is durable, incombustible, affordable, and long-lasting. Hence, this construction area is attracting lots of attention from researchers to practice sustainable development goals (Naseri et al., 2020). With urbanization and industrialization, the insistence for houses has increased subsequently. Hence, raw materials are needed in large quantity for concrete production worldwide, which eventually leads to the generation of industrial wastes, agricultural wastes, and other types of solid wastes that can pose various threats to environmental issues (Aprianti S, 2017). To minimize the negative impacts of concrete waste generated through excessive usage of raw materials, AI can be seen as being used for managing usage of smart materials like complementary cementitious material, which can be both reliable and suitable for providing alternative result for promoting the environmental sustainability of industries as well as in national urban initiatives like smart cities (Aprianti S, 2017; Kar et al., 2019).

Concrete is the most used material in construction sectors but is also known as an environmental pollutant, which causes severe defiance for sustainability in areas like resource depletion, vast energy usage, and emission of greenhouse gasses. Therefore, efforts are required to address the issues of environmental impression to boost sustainability, building strength, cost, environmental effect, CO2 emissions, energy wastage, and resource consumption which are factors of sustainability (Naseri et al., 2020). Hany et al. (2020) highlight how the effect or impact of equipment manufacturing and utility energy consumption (like natural gas by electricity) by the SHDS has long term impacts. During the inventory cycle and impact evaluation stage using various databases, the input and output of the raw materials and various energy consumption are assembled during the construction and operation phase. Also, in construction, the transportation of goods to the site and the plant is considered a vital impact factor in operation which can be resolved using various models of artificial intelligence (Hany et al., 2020). Similarly, the vacant land of smart cities has lost chances of developing parks, greenways, community gardens, and more. The operation work of construction, condensation of clay, changes in drainage, and other land cutting caused the loss of soil potential to flourish itself and the establishment period of new plants (Dwyer and Childs, 2004; Kar et al., 2019).

AI can improve safety, productivity, quality, and other essential measures. It can take over many monotonous duties and can help in efficiently designing and planning models to decrease overall cost and consumption of resources, both physical and energy.

4.3.6. *AI and financial services*

The finance sector is making several advancements while dealing with large data sets of organizations and enterprises. Digital transformation has created a new challenge that can impact the finance function, the entire business activities of the enterprises, and several other dimensions of enterprises. Here, we need artificial intelligence to manage such a large set of data and the working of the organizations. According to Forbes, 70% of financial firms use ML to predict cash flow events, adjust credit scores, and detect fraud.

Long term survivability and competitiveness of firms depend solely on the financial status of the firms. Investors, policy makers, and other stakeholders are actively involved in evaluating the organization's performance concerning sustainability in various aspects like – the environmental, social, and economic performance of an organization (Yakovleva et al., 2012). Limited access to finance can pose severe challenges in various sectors like food and drink industries while handling routine work like daily routine operations, meeting increasing users' demands, and dealing with suppliers (Xu et al., 2018). Hence, we will explore several areas of AI in managing financial sectors for foreign direct investment in activities related to supply chain network. One of the basic reasons for the economic downturn of a nation is a shortage of funds for FDIs (Hu et al., 2019). The financial view shows financial agreement by which financial institutions procure receivables from selected buyers who have credit risk lower than the high credit risk buyers and is also helpful in making a connection with low-risk suppliers and allowing access to short term credit at a lower cost (Yu et al., 2016). Employing various AI algorithms can impact not only innovation and advancement but also affect the workforce diversity in FDIs, where employees are given training and new skills to get the work done (Olan et al., 2021).

The financial services sector also incorporates the various dimensions of AI and machine learning and an independent decision support system. Like now, digital finance services are also available 24/

7, and solutions are provided per the customers' requirements. AI also provides process automation, case handling, bot services, online assistance to customers, and their validations (Kushwaha et al., 2022). For example, companies use various AI-based chatbots for debt collection with an average coverage of 90%. This percentage will increase further for as many activities of organizations, reducing the consumption of physical resources deployed for these activities.

5. Discussion

This paper has examined the various types of AI employed in sustainability and how to use AI to bring change in this domain. In the present scenario, the population is a significant issue that causes mismanagement in the use of resources. We exploit our resources at a very high rate, leading to a devastating situation for the coming generation. In this sense, we need to address the various challenges, issues, and barriers associated with using resources and need a proper framework based on artificial intelligence and machine learning-based approaches for sustainable development practices (Cuypers et al., 2021; Suman, 2021). The study's primary goal is linked to sustainability, and analyzing the various approaches used to address environmental issues that have been raised surrounding waste management, energy conservation, healthcare improvements, innovative learning, natural resource management, supply chain management, nuclear, alignment of stakeholders' interests, and more in past researches (Suman, 2021; Pueyo, 2018).

Our review indicates (see Fig. 3) that DSS, RL, SVM, ANN, and CNN algorithms are highly used methods to improve various pillars of sustainability. For example, Yang et al. (2022) exploration on RL in production management; Pereira et al. (2022) investigation on supply chain using DSS method. Also, we have seen that the used cases employed at a significant scale for sustainable development practices includes clustering, classification, association rule mining, and regression to incorporate artificial intelligence and machine learning in sustainability (Ko et al., 2016). Clustering helps in segmenting groups into a similar bunch called clusters. Classification implies predicting and delineating input data to an existing set of information and data. Association rule mining establishes relationships between various entities of AI models. Regression helps establish a relationship between one or more independent and dependent variables. From our findings, we observed that in the transportation sector, there are maximum papers and are using a supervised learning approach by using classification as a used case. For organizations employing artificial intelligence in the healthcare sector, mining is still in a very nascent phase, with 1% of work in this sector.

To illustrate the most frequently used methodologies for improving sustainable development activities, we have plotted a graph for all range of methodologies that have been employed till now in sustainability. However, our study accord with the past research that many new algorithms like Adaptive Neuro-Fuzzy Inference Systems (ANFIS) (e.g., Yani et al., 2022 used explore ANFIS; Zayed et al., 2021 to explore renewable energy), Binary tree, gradient boosting, random forest, and more are still to be explored to implement by the organization to improve the overall performance, as these methods have gained considerable attention by many research domains. However based on gaps in the existing literature and developments in machine learning in general, we foresee that methods like federated learning and tiny machine learning models may become extremely valuable in the years to come, given how they facilitate computing on edges and consume less power and minimize data exchanges over internet. The applications of these methods are yet to be documented in literature for sustainability.

The systematic literature review aimed at addressing three fundamental areas of sustainable development. One was to investigate the range of algorithms used in AI and sustainability. The second was to understand better the issues, opportunities, and barriers deemed significant for SD while using AI. The last was to establish how AI impacts SD and the nature of such impact.

5.1. Contribution to literature

In this, we have analyzed various aspects of existing papers on the uses of artificial intelligence and machine learning in sustainability:

1. The existing research papers highlighted that sectors like transportation, energy, medical, IT, education, food sector, services, construction, and manufacturing are extensively harnessing the power of artificial intelligence for sustainable development (Shi et al., 2019; Di Vaio et al., 2020). However, areas like mining, trade, agriculture and forestry, public administration, and finance need more research to exploit the real potential of these sectors. Hence, this study can help understand the AI uses in various industries.
2. In Fig. 7, we have presented a schematic diagram showing the relationship between various methods that various sectors of the economy are using, use cases, and the type of industry. We represented the industries using color coding; for example, green color represents the construction industry, red color represents the public administration sector, yellow represents service sectors, violet represents agriculture/forestry/fishing sectors, and more. Similarly, we have used number coding to represent the use cases. This diagram can help locate which methodology and use cases are used in which sector of industry and which sectors are yet to be explored using the given methodology.

The study illustrates that the industrial sectors based on SIP, that are increasingly employing artificial intelligence are transportation, communication, electric, gas, and sanitary services. This sector is extensively using methods like binary logistic, logit leaf, decision tree, LSTM, DNN, KNN, Linear Programming, Conway-Maxwell, Delphi techniques, Monte-Carlo, game theory and sensitivity analysis using use cases majorly classification, regression, clustering, association, RL, ensemble, anomaly detection, and deep learning. However, the use of NLP and sequence mining-based model is yet to be explored in this sector.

Further, the subsequent findings suggest that non-classifiable sectors (IT, environment, water, agriculture) is second most used sector that is using AI for improving their performance and output. This sector has employed almost all the AI based method using the combination of various used cases. The diagrammatic representation (Fig. 7) suggest that this sector need to adopt more innovative methodology like NLP, semantic web services, swarm intelligence, additive model to improve the overall harvest (precision agriculture), solving water contamination and water scarcity problem by detecting contamination level, identifying land surface patterns, and other contribution to climate change using various used cases.

Similarly for other sectors we can use this diagram to locate the use cases and AI based method use in the given industries and which sector need to incorporate the emerging technologies to make the sustainable development practices more resilient.

5.1.1. Criticisms of AI in light of sustainable operations of firms

Consumer security and privacy, AI biases, personal autonomy, wellbeing, and concerns with unemployment are some crucial subjects that need to be acknowledged by companies and firms around the globe. To support the sustainable growth of nations, businesses that employ AI systems must be socially responsible and make AI systems as secure as feasible. With real-time tracking and monitoring, diagnostic maintenance, precise forecasting and sales data, tailored marketing, waste control and overproduction, better achievement in sustainability performance and increased opportunity for the reuse and recycling of waste products/packaging, IoT implementation benefits the supply chain (de Vass et al., 2021).

AI has also been criticized in light of how systems based on AI need a lot of processing power thereby increasing energy consumption. The amount of data we need examine raises the cost of servers and high amount of electricity required to keep data centers cool. An organization will consume more energy as a result of the implementation of AI. Without knowledge of the potential environmental implications of future AI initiatives, it is impossible to periodically evaluate the investment one has made in any project. Also in coming time, the impact of AI on CO2 emissions must be a key factor in your decision-making (Gow, 2020; Dwivedi et al., 2022).

Determining the potential of Industry 4.0 (I4.0) digital technology to propel successful sustainability activities among companies in the future is much needed area. These technologies have the potential to minimize waste production, use less energy, and improve recycling and industrial symbiosis prospects, among other sustainability advantages (Akbari and Hopkins, 2022).

5.2. Limitations

This study entails some limitations which can pave the path for future research. First, this review has considered only article and review papers, which eventually reduced the number of papers in review. Hence, in future more diverse paper can be considered by researcher. Second, a single qualitative based review is not enough to map the all the dimensions of AI in sustainability. Third, researchers can expand the word search related to AI and sustainability in Scopus.

5.3. Future research directions

The findings of the paper indicate that most of the research is performed around Transportation/Communication/Electric/Gas/Sanitary services. However, there are very few researches in the area like Mining, Wholesale Trade, Public Administration, agriculture, forestry, and fishing. These areas can be a future scope for further study in AI and sustainability. Also, researchers can explore algorithms like Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Binary Tree, Gradient Boosting, Random Forest, Clustering, Ant Colony, Heuristic, and Sensitivity Analysis-to study the impact of AI on sustainable development practices. Further referring to Fig. 6 researcher can explore these algorithms using use cases like Sequence Mining, Anomaly Detection, Natural Language Processing, Ensemble, Association, and Deep learning. It is based on the findings of comparative analysis of the selected literature, a future direction of impact of AI on sustainability has been proposed.

In Fig. 7 we presented a systematic graph indicating the used cases and algorithms used by various industries. We have analyzed that algorithm like NLP is mostly used in manufacturing sector while LSTM algorithm is used in manufacturing, non-classifiable (IT, Environment, water, agriculture) and transportation sectors for cases like RL, classification & regression, and association. Further, DNN and RNN algorithm is used with classification & regression in industries like transportation, non-classifiable. However, application of DNN is not studied for service sector, while RNN is not explored in construction sector. SEM is used with regression, classification, and association in industries like manufacturing, services, and other non-classifiable sectors. Similarly, Taguchi algorithm is used with classification & regression in area like manufacturing. SVR algorithm is used with NLP, regression, and ensemble in industries like construction and other non-classifiable sectors. From Fig. 7, researchers can take inference for future research by exploring new algorithms in different areas using various use cases. Like in NLP almost all type of industries is yet to be explored including manufacturing sector. Similarly, LSTM algorithms are still in nascent stage of exploration by various industries like mining, services, administration and more. This information can be very helpful for future research and help in maintain sustainable development in true sense.

In the future research methods like Federated learning and TinyML have lots of scopes in area of sustainability. Federated learning works efficiently on decentralized servers holding large amount of local data sets without exchanging data among them. It reduces strain on network and also ensures privacy among devices and organization. Usually, a machine learning algorithm consumes lots of energy and requires lots of computational power. For example, processing single model of deep learning method can generate CO2 as much as lifetime of five cars (Li et al., 2020). This may possess serious environmental issues. In such cases federated learning may show practical solution for sustainable development practices (Li et al., 2020).

TinyML has brought machine learning power to the edge of advancement. The biggest reason we are now shifting our focus towards TinyML is sustainability. It is an intersection of low power embedded system and machine learning where the compute resides in the edges. It is called as next generation AI (Han and Siebert, 2022). As carbon emission has increased significantly with the advancement in AI, hence we require more energy efficient computational algorithms for sustainable development practices. To mitigate these challenges TinyML stand out in reaping most rewards by performing efficient computing. It offers a sustainable method to reduce our carbon consumptions and usage. Till now it has received very little attention because of some constraints associated with microcontroller units. However, this has potential to improve the efficiency of available devices in a long run.

6. Conclusion

This research aimed to determine the impact of artificial intelligence on sustainability and the algorithms used therein, as well as various industries where artificial intelligence is employed to address the issues of various domains using different use cases. In doing so, we defined key terms and a table on the impacts of AI in various sectors. Also, we have offered a pictorial representation of the kind of studies performed till now, methodologies employed in addressing sustainability issues, and different sectors where the use of AI is prevalent are presented. Within these topics we also highlighted the problems to guide further work in each area. We call on researchers and practitioners to explore more in this area and think more about opportunities and issues associated with this area. The ideas and suggestion presented in this paper are not intended to be definite, but hopefully graphs and tables can give ideas to future researcher on how to engage themselves in this domain.

In our study, we have tried to cover all the sectors of SIP-based industries and the effect of AI on their sustainable management practices. These industries are classified, and the corresponding use of AI in these sectors is identified. The quantitative data reveal that the, classifiable sectors, non-classifiable sectors, manufacturing, construction, and services have significantly adopted the AI-based methods to improve their SDG practices. Out of all the papers based on AI and sustainable practices, we found that 74% of industries are using supervised and unsupervised based algorithm. However, the proposed framework is still in nascent stage because sustainable management practices require time, and incorporating these practices using AI requires high computational efficiency. We have listed all the technologies that have been used till far for sustainable management practices.

The model developed in this research will be insightful for researchers and practitioners who want to further research in this area. Using the information provided above, researchers can find gaps in current papers on the adoption of AI in SDG and further can-do research.

Statement of contribution

All authors have contributed in the development of this literature review and all contributors have been listed as authors. The first author led the development of the study from conceptualization, research protocol, writing parts of the review to editing the manuscript after the review was undertaken. The second author undertook the analysis and writing of the findings. The third author helped in writing part of the manuscript including editing it.

Author statement

Dear Editor in Chief.

The authors declare the following for the current submission.

• The article is not submitted anywhere else and will not be submitted till this journal takes a decision.

• Declarations of interest: none

• There is no conflict of interest.

• Attempts have been made to use inclusive languages wherever possible.

• All authors have contributed, and all contributions have been acknowledged

• The study is exempted from the approval of the ethics committee

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

List of Methods
DECISION TREE; RANDOM FOREST; REGRESSION; MONTE CARLO; GENETIC ALGORITHM; HIERARCHICAL BLOACKCHAIN FRAMEWORK; SEM; CNN; BAYESIAN; LSTM; RANDOM MULTINOMIAL LOGIT MODEL(RMLM); BLOCKCHAIN; RNN; EXTREME GRADIENT BOOSTING; (XGBOOST) ALGORITHM (TREE BASED ALGORITHM); SEMANTIC WEB SERVICES (SWS); SUPPORT VECTOR REGRESSION; RANDOM SURVIVAL FOREST; BOOTSTRAP SAMPLING; DATA DRIVEN- CHANCE CONSTRAINED PROGRAMMING; HEURISTIC; SENSTIVITY ANALYSIS; DSS; KNOWLEDGE-BASED SYSTEM USING THE COMMONKADS (CKADS); SENSITIVITY ANALYSIS; ANN; MIXED-UCT (MONTE CARLO TREE SEARCH); DRL; (DEEP Q-NETWORKS (DQN) AND DOUBLE DEEP Q-NETWORKS (DDQN)); SPATIOTEMPORAL DEEP LEARNING APPROACH; CLASSIFICATION; GAUSSIAN PROCESS (GP) REGRESSION; METAHEURISTIC; KNN; MULTI-CRITERIA DECISION ANALYSIS (MCDA); N-BEST LIKELIHOODS; SVM; N-BEST LIKELIHOODS; ADAPTIVE LEARNING; PROFILING ALGO; DESCRIPTIVE STATISTICAL ANALYSIS; SMO; ADABOOST; DATA MINING; MULTIVARIATE ADAPTIVE REGRESSION SPLINES(MARS); RNDOM FOREST; ANT COLONY OPTIMIZATION (ACO); ANALYTIC HIERARCHY PROCESS; AUGMENTED REALITY; DEEP ABNORMALITY DETECTION; DNN; COMMON METHOD VARIANCE (CMV); EVOLUTIONARY LEARNING; ADVERSARIAL MACHINE LEARNING; SELF-ADAPTIVE LEARNING; DEEP REINFORCEMENT LEARNING; MARKOV PROCESS; Q-LEARNING; AUTOMATIC MODELLING; LP MODELS; MARKOV DECISION PROCESS; K-MEANS ALGORITHM; MARKOV CHAIN MODEL; HIERARCHICAL CLUSTERING ANALYSIS; REGRESSION; SEMANTIC NETWORKS; SVR; EXTREME GRADIENT BOOST; POLYNOMIAL REGRESSION; Q-NETWORK (DQN); PREDICTION METHOD; MULTIVARIATE ADAPTIVE REGRESSION; CONWAY-MAXWELL-POISSON; ADDITIVE MODELING; REGRESSION; ORDINARY LEAST SQUARES ANALYSIS; LINEAR AND GENERALIZED ADDITIVE MODELS; GRADIENT BOOSTING GREY RELATIONAL ANALYSIS; TAGUCHI METHOD; POISSON MODEL; MULTI CRITERIA DECISION MAKING; GRADIENT BOOSTING; LCC-MEC; BRL; FOG-BASED IDENTITY AUTHENTICATION (FBIA) SCHEME; DEEP LEARNING; LINEAR MIXED-EFFECTS MODELS; BOOSTED REGRESSION TREES; MULTI-AGENT SYSTEM; SVD; PERCEPTION AND HIERARCHY-ELM; FIXED DICTIONARY EXTREME LEARNING MACHINE (FD-ELM); LOCATION-BASED AUTHENTICATION SYSTEM (LOCAUTH); RSSI BASED NEAREST NEIGHBORS (RSSI-BASED NN); GESTURE RECOGNITION ALGORITHM; MACHINE COGNITION (MC); DELPHI METHOD; HUMAN-ROBOT COLLABORATIVE DISASSEMBLY (HRCD); MODIFIED SOIL-ADJUSTED VEGETATION INDEX (MSAVI2); NORMALIZED DIFFERENCE INFRARED INDEX (NDII); BI-LEVEL DECISION SUPPORT SYSTEM (DSS); SENSTIVITY ANALYSIS; DYNAMIC PROGRAMMING (DP); SWARM OPTIMISATION; SME; MAXIMUM ENTROPY (MAXENT); GENETIC ALGORITHM RULE-SET PRODUCTION (GARP); LEARNING CENTRIC WIRELESS RESOURCE ALLOCATION (LCWRA); MEL FREQUENCY CEPSTRAL COEFFICIENTS (MFCC); LINEAR AND PREDICTIVE CEPSTRAL COEFFICIENTS (LPCC); SMA; MAB; GAME THEORY; TDNN; MACHINE LEARNING BASED SECURE CLOUD JOB SERVICES (MLSCS); REINFORCEMENT LEARNING BASED DEEP Q MATRIX (RL-Q MATRIX); AUTHENTIC VPC CONFIGURATION; DNN; MLP; MULTIPERIOD GRID COMPUTING NETWORK OPTIMIZATION FRAMEWORK; ADAPTIVE BOOSTING (ADABOOST); K-MEAN CLUSTERING; REINFORCEMENT LEARNING; MULTI-CLASS RESAMPLING METHODS (SMOTE); ATSC ALGORITHM; ALBIDS (ADAPTIVE LEARNING STRATEGIC BIDDING SYSTEM); MULTIPLE ADDITIVE POISSON REGRESSION TREES (MAPRT); DEEP NEURAL NETWORK; REDUCED TRAINING VECTOR-BASED SUPPORT VECTOR MACHINE (RTV-SVM); UIPATTERNM MODEL; AMBIENT INTELLIGENCE (AMI); NLP; LOGIT LEAF MODEL (LLM); TPMA; RF; MULTI-WAY PRINCIPAL COMPONENT ANALYSIS (PCA); KNOWLEDGE RESTRICTED BLACK-BOX ATTACK MODEL; TOPIC MODELLING AND TEXT MINING (REAL-TIME CRASH PREDICTION MODEL); (KERNEL FUZZY C-MEANS); MARKOV DECISION PROCESS (MDP); SEQUENTIAL; SVR; MINING; MULTINOMIAL LOGIT MODEL; ANP; MCDA; SET-THEORETIC COMPARATIVE APPROACH; PATH MODEL; ADAPTIVE NEURO FUZZY INFERENCE SYSTEMS (ANFIS); CMV; LOGISTIC REGRESSION

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