

Fundamentals of Artificial Intelligence: A Review

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Abstract— From last two to three decades, Artificial Intelligence has gained so much attention from government, industry and academia. The technological and industrial revolution is accelerating by the widespread application of new generation information and communication technologies, namely AI. In this research article, a systematic literature review (SLR) is performed and discusses the artificial intelligence concept. It includes numerous definitions of AI by different researchers, a comprehensive life cycle for the design, development, and deployment of artificial intelligence (AI), distinct types and techniques of AI along with its challenges. The literature studies is performed from 82 research articles via well-known databases such as Scopus and Web of Science, Google Scholar, IEEE Explorer and Science Direct. The outcome of this article can play a role in AI related research and should provide important insights for new entrants to the artificial intelligence area.

Keywords— artificial intelligence, CDAC AI life cycle, machine learning, deep learning

I. INTRODUCTION

The concept of "Artificial Intelligence" was first introduced by John McCarthy in 1955 as part of a proposal for the Dartmouth Summer Research Project on Artificial Intelligence, which he co-authored alongside Marvin L. Minsky, Nathaniel Rochester, and Claude E. Shannon [3]. AI is characterized by systems that exhibit intelligent behavior through environmental analysis and autonomous actions aimed at achieving specific objectives [1]. The discipline encompasses a diverse array of methodologies and tasks; some have been effectively solved through software applications, while others still necessitate extensive research efforts. AI is crucial for societal advancement, yielding transformative outcomes in enhancing labor productivity, lowering labor expenses, optimizing human resource structures, and generating new employment opportunities. The rest of the paper is structured as follows: distinct explanations of AI by various researchers, CDAC AI life cycle and types of AI is addressed in Section II. Section III describes AI techniques. Section IV illustrates the AI challenges and Section VI concludes the paper.

II. LITERATURE STUDIES

A. Understanding the Artificial Intelligence

Artificial intelligence's integration in community requires to understand what is an artificial intelligence, in what ways has technology advanced and now, what is the current state of artificial intelligence. In [4], authors mentioned and discuss that defining the artificial intelligence is not easy as there is no commonly recognized definition of AI.

Various different definitions of artificial intelligence are used by different authors in their research work which can easily lead to confusion. The sheer diversity of definitions of

AI is not because of carelessness but inherent in the phenomenon of AI itself. So, it is very significant to illustrate the concept of artificial intelligence appropriately. For this, a systematic literature review is performed to discuss and presented the numerous distinct definitions of AI from different authors.

The generous definition of AI is defined with algorithms. Algorithms predate AI and have been broadly used outside the field of AI. The term "algorithm" is derived from the name of the ninth-century Persian mathematician Mohammed ibn Musa al-Kharizmi and "algorithm" defined as particular set of instructions to solve the particular problem or performing a calculation. So, if AI will be defined as the use of algorithms, it would contain various other activities, for instance operations of a pocket calculator or even the instructions in a cookbook. In the strictest definition of AI, it defined as imitation by computers of the intelligence inherent in humans. Purists point out that various present applications are still relatively simple and therefore not true artificial intelligence. This composes this definition inaccurate too, the usage of this definition would imply that Artificial intelligence does not exist at present.

A popular definition of artificial intelligence is a technology that allows machines to mimic a variety of complex human skills. However, this does not provide much information. In actuality, it merely uses different terminology to refer to "artificial intelligence.". The precise nature of artificial intelligence is still unknown as long as those "complex human skills" are not defined. The definition of artificial intelligence (AI) as the ability of computers to perform complex tasks in complex environments is also applicable.

Other interpretations delve deeper into the explanation of these abilities and duties. For instance, computer scientist Nils John Nilsson characterizes a technology that "operates suitably and with foresight in its environment [5]." In addition, some individuals refer to the capacity to sense, pursue objectives, initiate actions, and learn through a feedback mechanism [6].

A comparable explanation has been provided by the High-Level Expert Group on Artificial Intelligence (AI HLEG) of the European Commission (EC): "Systems that exhibit intelligent behavior by analyzing their surroundings and taking actions—with a certain level of autonomy—to achieve specific goals [2]." These task-oriented definitions enhance our comprehension of what constitutes AI; however, they are not without their drawbacks. Phrases like "a certain level of autonomy" remain rather ambiguous. Furthermore, these descriptions tend to be excessively broad since they encompass phenomena that many would not typically categorize as AI. For example, Nilsson's description is also applicable to a

traditional thermostat. This device can perceive (measure room temperature), pursue goals (maintain the set temperature), initiate actions (adjust the thermostat), and learn from feedback (cease operation once the desired temperature is attained). Nonetheless, most individuals would not consider a thermostat to be an example of AI.

AI is so hard to define precisely is not surprising. After all, it is a simulation or imitation of human intelligence, which we still do not fully comprehend [7, 8]. Psychologists, behavioral scientists, and neurologists, among others, have long studied this. Although our understanding of intelligence and the human brain is extensive, there is still disagreement over the precise definition of human intelligence. It is impossible to pinpoint exactly how that intelligence can be artificially replicated [9]. In the research paper [10], authors mentioned that modern technology does not provides us intelligence but only one of its components.

Going a step further, philosopher Daniel Dennett says we shouldn't even model AI on humans. Instead of being artificial people, these are a brand-new kind of entity and one he compares with oracles: entities that can make predictions but, in contrast to humans, lack a personality, conscience, or feelings [11]. Stated differently, artificial intelligence (AI) does something different from what humans do. The question "Do submarines swim?" was used by Edsger Dijkstra to demonstrate this [12]. Though it would be incorrect to refer to what these boats do as swimming, it is comparable. Artificial intelligence (AI) is capable of performing tasks that appear to be intelligent but are actually quite different.

Lastly, the newest technology is frequently associated with artificial intelligence. AI has become extremely popular in the last few years. Progress in one particular area of the field, "machine learning" (ML), has been one of the main drivers of this. Innovation in this area has led to what is now known as "deep learning" (DL). This technology is responsible for recent innovations like computers that can play games like Go and recognize faces. In contrast to more conventional methods, which use fixed rules applied by computer systems, machine learning and deep learning algorithms are able to identify patterns in data. In this context, we also refer to "self-learning algorithms.". When many people discuss AI these days, they are really talking about these algorithms, and frequently DL in particular. It is crucial to concentrate on this technology because it raises a number of urgent AI-related issues, including explainability issues.

In the [1], authors have settled on an open definition of AI. Two factors are relevant in this respect. Firstly, it would be inappropriate to restrain the definition of AI to a specific part of the technology. For instance, we were to confine ourselves to 'deep learning' as discussed above, we would ignore the fact that many current issues also play a role in other AI domains, such as logical systems. Secondly, because of the nature of this scientific field, as was previously mentioned, the definition of artificial intelligence will inevitably evolve over time.

Instead of viewing AI as a clearly defined discipline with simple definitions and established methodologies, it is more beneficial to regard it as a multifaceted and intricate field oriented towards a specific objective. This objective is represented by the aspiration to comprehend and replicate all

human cognitive abilities. This aim is often referred to as 'artificial general intelligence' (AGI), with alternative terms including 'strong AI' and 'full AI'. Nonetheless, it remains uncertain if this goal, characterized by such a broad definition of AI, will ever be achieved. The majority of specialists believe that we are still several decades away from its realization—if it can be realized at all [13].

The authors [1] outline AI as encompassing the entire spectrum of applications that are currently being implemented or are anticipated in the near future. The definition provided by the AI HLEG allows for considerable flexibility in scope. By characterizing AI as "systems that exhibit intelligent behavior through environmental analysis and action-taking—with a degree of autonomy—to fulfill specific objectives," this definition covers all applications presently categorized as AI while also accommodating potential future modifications to that classification. In addition to advanced machine learning and deep learning technologies, this definition includes other methodologies, such as traditional approaches utilized by various governmental organizations. In summary, this definition is precise enough to differentiate AI from algorithms and digital technologies broadly while remaining sufficiently adaptable to incorporate future innovations.

B. CDAC Artificial Intelligence life cycle

The next significant steps to understand the artificial intelligence is to grasp how the AI functioning. In the sytomatic literature studies, numerous sources presented and discussed the different number of stages to demonstrate the working of artificial intelligence. In this research article, the "CDAC AI life cycle," a comprehensive life cycle for the design, development, and deployment of artificial intelligence (AI) systems and solutions is considered and discussed [15]. In addition to focusing on the difficulties of risk analysis of AI adoption, transferability of prebuilt models, the growing significance of ethics and governance, and the makeup, expertise, and knowledge of an AI team necessary for successful completion, it fills the gap in a practical and inclusive approach that goes beyond the technical constructs.

The 'CDAC AI life cycle,' is presented as the progression of an AI solution through its distinct phases namely design, develop, and deploy and 19 constituent stages from conception to production as applicable to any AI initiative as shown in Fig. 1.

As shown in the same figure, each phase calls for a distinct set of human skills, such as design (AI/data scientist), development (AI/ML scientist), and deployment (AI/ML engineer).

A senior position with several years of experience is usually held by the AI/data scientist assigned to the design phase. They should be able to identify the issue and then come up with a solution based on the body of knowledge already in existence as well as their prior experience working on a variety of AI projects. When they deliver a prescriptive problem formulation, solution description, and representative data to the AI/ML scientist in charge of the develop phase, they should also be able to identify the representative data, required data, and available data by working through the first five stages of the life cycle. A junior position that is more technical and less conceptual, this AI/ML scientist usually has

extensive technical knowledge of AI algorithms, model development, and evaluation. The next seven steps will be

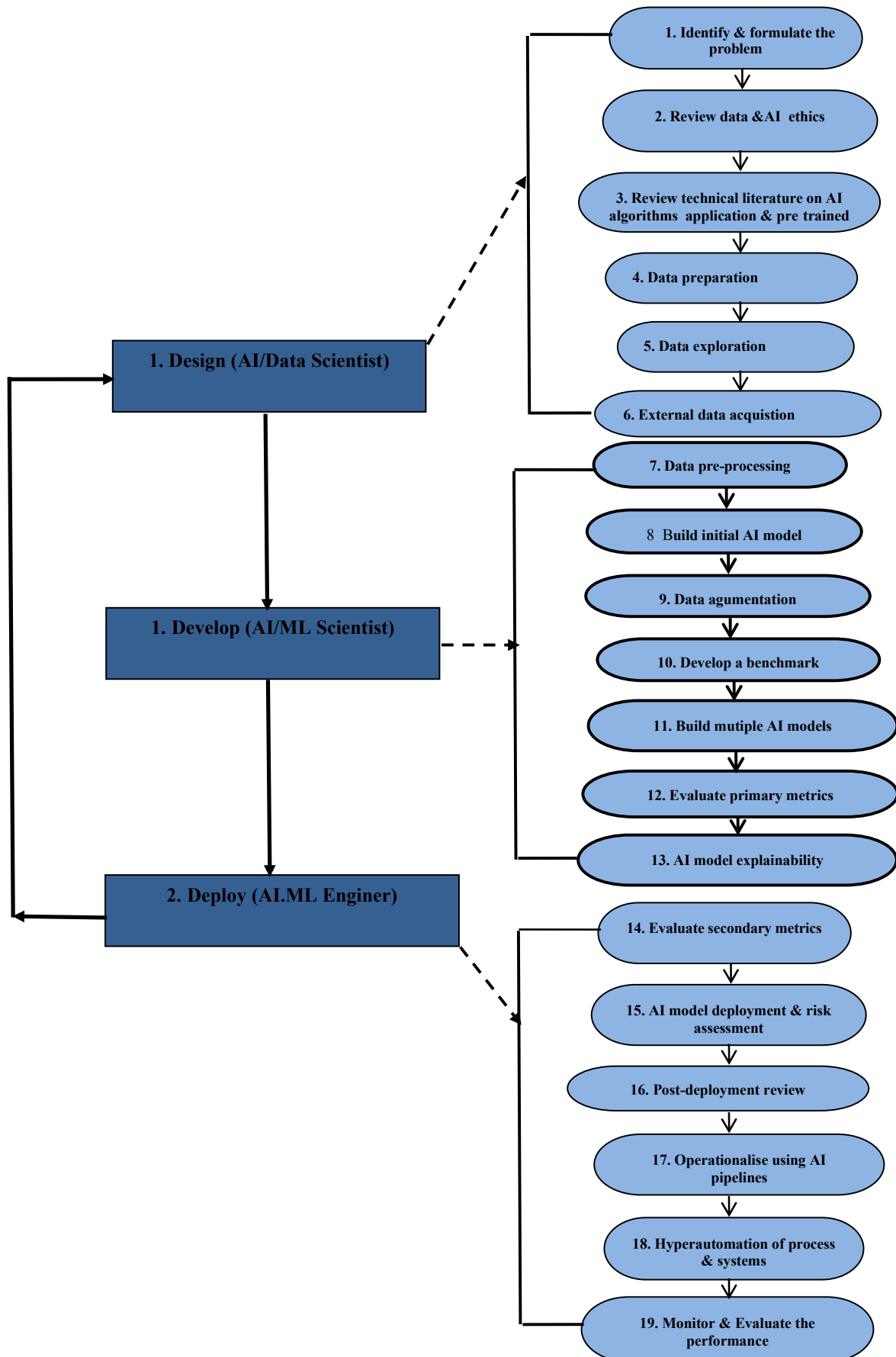


Fig. 1. CDAC Artificial Intelligence Cycle

used to turn the problem formulation into a prototype AI model. This prototype AI model is then further transformed by an AI/ML engineer during the deploy phase into a deployed service or solution that is standardized for access by all stakeholders and end users. Usually, the AI/ML engineer comes from the DevOps field. Although the skills needed for this phase are common, they must be combined with expertise in the subtleties of implementing AI models, as DevOps is a well-established practice in software development and IT operations. The AI/ML engineer will complete the last seven steps to produce an AI solution that is a component of a bigger process and can be automatically assessed for accuracy and quality using a number of metrics. It may be necessary to hire or contract for several of these positions, depending on the project's size, scope, and scale. Additional enabling roles that contribute to the AI endeavor's value, inclusivity, and quality include an ethicist (or ethics committee), a project manager, a group of domain experts, a participatory design group, a pilot study cohort, legal counsel on intellectual property law, and a steering/advisory committee with complete oversight. The type of project, project timelines, organizational data maturity, and AI expertise all affect how all 19 stages are carried out. To successfully complete an AI project, all stages must be carefully considered and formally documented, even if only a portion of them are completed.

1) *Identify and formulate the problem*

Finding, clarification, and formulating the problem in terms of its typology, environment (or setting), expected goal, people (or stakeholders), systems, processes, and data is the first step in the life cycle. Typology can be broadly categorized as research, tactical, strategic, and operational.

2) *Review data and AI ethics*

This step involves cross-examining and validating the problem formulation, chosen approach, possible solution, and necessary data sets for ethical and legal compliance as well as potential security risks (referring back to the preliminary risk assessment). Since the AI team has a very technical skill set, professional ethicists with the necessary theoretical and practical experience must conduct this ethics review.

3) *Review technical literature on AI algorithms, applications, & pre-trained models*

The problem formulation offers the background information required to investigate and evaluate published studies, implemented systems, solutions, and libraries that have been used in comparable contexts [39]. Some of the more popular sources of information include research article search engines (e.g. A. Google Scholar), publications (e.g. A. medium), Q&A websites (e.g. A. g. Stack Exchange), code archives (e.g. A. g. cloud platform providers (e.g., GitHub), A. AWS, GCP, Azure), and social media (e.g. A. (Twitter)). Literature reviews, commentary, letters, articles, op-eds, case studies, best practices, product/tool documentation, tutorials, demonstrations, API documentation, and answers, upvotes, and likes on Q&A forums are just a few of the many types of resources available. Furthermore, rather than creating a new AI model from scratch, recent advancements in open-access pre-trained models like AlexNet [16], ResNet [17], BERT[18], and

GPT [19] should be examined to learn and investigate how they can be repurposed, retrained, or fine-tuned.

4) *Data preparation*

Before developing AI models, it is advised to design and create a unified data repository, such as a datawarehouse [20, 21] datalake [22], or data lakehouse [23, 24, 39], which centralizes data access, ownership, stewardship, metadata, data ethics, governance, and regulations.

5) *Data exploration*

Unlike the previous stage, where the focus was on the data structure, this stage is more concerned with the actual data. Usually, the stage starts with a comparison with algorithmic baselines and industry benchmarks that have been documented in the literature and where comparable issues have been solved. Real data is added to the data structure created during the preparation stage using methods like data visualization, correlation analysis, data granularity alignment, examining the connections between data points and attributes, managing outliers, and implementing data quality checks.

6) *External data acquisition*

When combined, the stages of data preparation and exploration can reveal data limitations that render the development of AI models impractical. In this case, it is important to look into possibilities for obtaining data from outside sources. One common short-term tactic is to obtain the necessary data in aggregate or detailed form from data brokers and data vendors. These brokers and vendors gather vast amounts of data by using public records, credit scoring services, social media content, and third-party data sharing agreements. These data are then marketed as aggregate products, like health care or socio demographic profiles.

7) *Data pre-processing*

With the least amount of compromise to accuracy, informational value, and data quality, the data pre-processing stage guarantees that all the data collected to construct the AI model or application can be accurately input into the AI algorithm. This includes formatting, transformation, and imputation.

8) *Build initial AI model*

By identifying an appropriate AI algorithm that reflects the AI capabilities corresponding to the AI application, this step starts the development of an AI model. One or more of the four capabilities—prediction, classification, association, and optimization can be applied to all current real-world applications. It is advised to start with "applications" before moving on to "algorithms" via "capabilities" when deciding which algorithm to use to construct the model.

9) *Data augmentation*

Data augmentation addresses limitations in the data set that impact the model's output, based on the output and devaluation of the original model. The original model will be run multiple times as the efficiency of the augmentation measures is assessed, in contrast to data transformation, which is specific to variables and includes class imbalance, feature engineering, and feature representation. Undersampling and oversampling techniques are commonly

used to address class imbalance, [25, 26], whereas feature engineering and feature representation are broad topics that span various fields of study, including signal processing techniques, vector symbolic architectures, [27,28, 29–31], and dynamic time warping [32, 33].

10) Develop a benchmark

The development of the first AI model necessitates the consideration of an appropriate evaluation benchmark. A common-sense heuristic, such as human expertise in solving the same problem (for example, anomaly detection) or the success rate of the human expert in detecting anomalies using the same input data, is usually used to determine this benchmark. As an alternative, the industry sector or the literature related to the same algorithm may serve as the benchmark. The benchmark not only evaluates the model but also determines which input vectors or attributes do not fit the model. If the data are an incomplete representation of the problem domain, the benchmark returns to the data pre-processing stage or moves on to the next stage of building multiple models.

11) Build multiple AI models

The maturity of the AI field, particularly with regard to build technologies like Jupyter notebooks and the availability of feature-oriented algorithms as code libraries on repositories like GitHub, has made it possible to build multiple AI models quickly and effectively. To guarantee that the developed application is legitimate and lawful, licensing for distribution and reuse, specifically in code repositories and any third-party content, must be followed and documented. Alternatively, these algorithms can be swiftly re-implemented without the limitations imposed by the code repository license via modern programming languages like Python.

12) Evaluate primary metrics

The primary metrics build on the performance benchmark determined earlier. Understanding what the metric represents and how it is calculated is crucial, and this information can be found in a variety of literature, including case studies and API documentation. Accuracy, robustness, agnosticism, scalability, and interpretability are all important characteristics of an evaluation metric. Metrics like accuracy, precision, recall, F1 score, root mean-squared error, purity, and entropy are frequently utilized. The common misconception that "accuracy" is the only performance metric worth taking into consideration and choosing an appropriate metric when there are numerous options is addressed by the generalized formulation of a performance metric, $\text{outcome} = \text{model} + \text{error}$. The evaluation metrics are also helpful for determining the bias variance trade-off and comparing all models across default and fine-tuned parameter settings.

13) AI model explainability

Explainable AI [XAI], also referred to as model interpretability or model explainability, is a relatively new development motivated by the ethical and legal need to make AI transparent. However, explainability has also benefited model development since AI scientists are better able to understand how model parameters, the learning process, and the intricacies of attributes contribute to the desired AI result.

For complex models (like gradient boosting or neural networks), where the flow of information from input vectors to decision output is obscured by numerous layers of distributed (or partial) computations, AI transparency is necessary.

14) Evaluate secondary metrics

At this point, the AI scientist gives the AI/ML engineer a prototypical and working AI model. The AI model must be computationally efficient in order to be deployed or operationalized for a wider audience, in addition to effectively demonstrating "intelligence" in completing the task. Consequently, this stage involves the calculation of a number of secondary metrics, including convergence metrics, time-complexity, memory performance, computational (CPU) performance, and ethical implications.

15) AI model deployment and risk assessment

This stage, which is also referred to as model scoring, model production, or model serving, involves deploying the evaluated model for operational use. It is smaller in scale to "operationalization". Instead of granting access to the entire organization, deployment would usually involve a smaller group of specialists and users. The number of end users and types of applications, the expected output formats, the anticipated turnaround time, the frequency of use, and real-time versus batch use of the AI model are the main factors to take into account when deploying the mode

16) Post-deployment review

An expert panel, steering committee, or regulatory body will perform a technical and ethical review of the entire project, from a datasets approach to an AI model to assess metrics and effectiveness, depending on the industry sector and project scope. This stage will also involve the administration of contracts, service level agreements, post-implementation documentation, compliance, and standardization. Particularly in the field of healthcare, additional research will be carried out through observational studies, small-scale clinical trials, training, and user-acceptance exercises. At this stage, the team will also take into account the legal protection of intellectual property through patenting or the alternatives of trade secrecy, which offers ongoing protection (as patents expire) or defensive publications in scholarly journals that advance the field.

17) Operationalize using AI pipelines

This stage, also referred to as MLOps or AI Ops, is an adaptation of the highly successful DevOps software automation capabilities into the deployment of AI models. DevOps, a product of the Agile movement, was defined by Dyck [34] as "a collaborative and multidisciplinary effort within an organization to automate continuous delivery of new software versions, while guaranteeing their Correctness and reliability.". Numerous survey articles have examined the benefits, drawbacks, and difficulties associated with DevOps [35, 36] and its integration with AI [37, 38].

18) Hyperautomation of processes and systems

To provide hyperautomated systems and processes, an operationalized AI service will be linked to a process automation pipeline as part of the AI lifecycle. To spark interest in a hyperautomation pilot phase, process owners and stakeholders both upstream and downstream must be shown the

capabilities of the AI solution. Following this pilot phase, the performance improvements in productivity, efficiency, and effectiveness must be measured and compared to earlier configurations to develop a business case for deployment at scale.

19) Monitor and evaluate performance

This final stage of the lifecycle will involve monitoring and evaluation of the AI model that has either been deployed independently or integrated as a hyper-automation process. The primary evaluation criteria are value created by the technology, diverse people using it in a variety of contexts, and representation of the technology itself. The people criterion is measured by end-user activity, the technology is assessed using model drift and model staleness, and value generation is measured by return on investment (ROI). Model drift, which indicates a decline in the model's accuracy as a result of the data's changing nature can be addressed by retraining the model with more recently collected data points that capture these changes or drifts. On the other hand, model staleness is caused by changes in the problem or environment description underlying the model design and development. Addressing staleness requires a fundamental rethink of the model architecture, inputs, algorithm, and parameters. A stale model will trigger a new iteration of the full life cycle.

Continuous monitoring of end-user activity is critical to find out if and how the model is contributing toward organizational functions. The level of end user activity depends on each use case and metrics can be drawn from adoption, questions, frequency of use, use/revision of documentation, feedback, and requests for features. Finally, although ROI is not directly visible like most other knowledge work, it can be determined using several types of metrics, such as reduced costs (due to reductions in turn around time, human effort, human skill), increased revenue (due to new revenue streams, customer satisfaction, increased market share), and productivity gains (such as reduced errors, low employee turn over, increased agility of teams, and work flow.)

III. ARTIFICIAL INTELLIGENCE TECHNIQUES

AI contains numerous major scientific areas, it includes Machine learning, natural language processing (NLP), text and speech synthesis, computer vision, robotics, planning, and expert systems. Fig. 2 illustrates the AI domains that the authors created using resources [40]. Many AI applications are based on machine learning techniques, which apply the core concepts of AI. ML is used to improve speech recognition [41] and speech emotions [42]. Economic planning [43] and factory control [44] employ a variety of machine learning techniques. According to Ref. [45], machine learning (ML) is a powerful data analysis technology that may be applied to a variety of expert systems. One of the primary focuses of robotics research at the moment is machine learning [46].

The potential of artificial intelligence is greatly explored via machine learning. The development of adaptable, flexible, and "teachable" algorithms or computational techniques is the primary expectation related to machine learning. New features of programs and systems are thus made available. Machine learning (ML) is a subset of artificial intelligence techniques that enable computer systems to learn from past experience (i.e.,

from data observations) and improve their behaviour to accomplish a certain task, according to the definitions provided

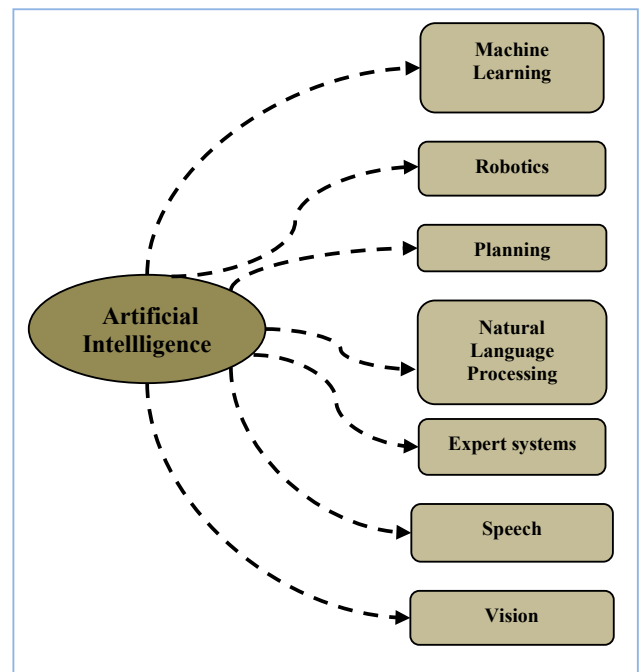


Fig. 2. Types of Artificial Intelligence

in [47]. Support vector techniques, decision trees, Bayesian learning, k-means clustering, association rule learning, regression, neural networks, and many more are examples of machine learning.

A subset of machine learning techniques, neural networks (NN) or artificial NNs have some indirect connections to biological neural networks. They tend to be defined as a collection of interconnected components arranged in layers and referred to as artificial neurones. A subset of NN called deep learning (DL) offers computation for multilayer NN. Deep neural networks (DNN), convolutional neural networks (CNN), recurrent neural networks (RNN), generative adversarial networks (GAN), and more are examples of common DL concepts. In [48–51], machine learning model classification was examined. ML techniques split into five categories [52] (Fig. 3) namely Unsupervised learning (UL) or cluster analysis, Supervised learning (SL), Semi-supervised learning, Reinforcement learning, and Deep learning.

1) Supervised learning:

The basis of this kind of machine learning is training the learning algorithm on labeled data.

Since the data is composed of pairs an input that can be represented by a vector and its corresponding desired output, which can be defined as a supervisory signal it is referred to as labeled [53].

Since the proper output is known, the learning algorithm tries to predict it iteratively and is adjusted to minimize the variation gap between its predicted and actual output, which is why the learning mechanism is referred to as supervised [41].

The supervised learning algorithm can generate a function that is referred to as a regression function if the output is continuous

and a classifier function if the output is discrete by analyzing the training data [53].

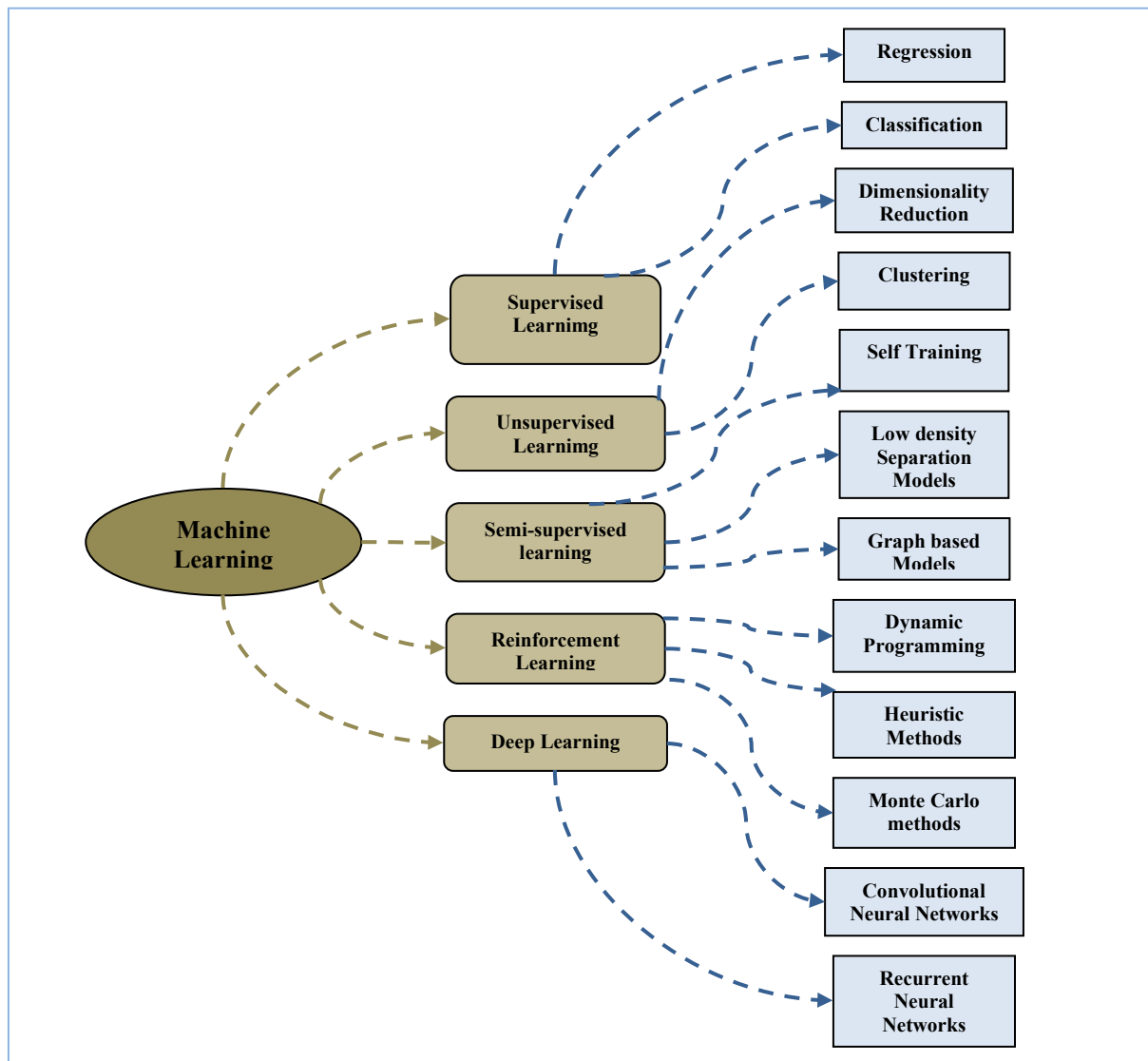


Fig. 3. Types of Machine Learning

The generated function predicts the output corresponding to every given input since the learning method reasonably generalizes patterns and characteristics found in the training data to new input data. The two primary types of supervised learning algorithms are classification algorithms (discrete output) and regression algorithms (continuous output). The goal of regression algorithms is to find the function that matches the training dataset's points. The three primary categories of regression algorithms are polynomial regression, multiple linear regression, and linear regression [53].

2) Unsupervised Learning:

In contrast to supervised learning, this approach trains the learning algorithm using an input dataset without any labeled outputs. Unlike supervised learning, there is no human intervention to make corrections or adjustments.

Consequently, compared to supervised learning, unsupervised learning is more subjective [54].

Finding the basic structure or distribution patterns present in the data itself is the primary objective of unsupervised learning. The algorithm learns on its own by reflecting the overall structure of input patterns and attempting to represent a specific identified input pattern.

As a result, the various inputs are grouped according to the characteristics that were taken from each input item [54]. Unlike supervised learning, this method uses an input datasets without any labeled outputs to train the learning algorithm. The method can create and distinguish between the resulting clusters, even though it won't give them names. It can also use some of these clusters to assign new examples to other clusters.

When sufficient data is available for usage, this method which is based on input data—can function effectively. Social information filtering algorithms, like those employed by Amazon.com to suggest books to users, are one example of that. Finding comparable groups of people and then adding new members to these groups is the foundation of these algorithms [54]. The three primary types of algorithms used in unsupervised learning are anomaly detection, dimensionality reduction, and clustering [44].

3) Semi-supervised learning:

In situations where we have a lot of input data, some of which are labeled and the remainder are not, this approach lies in the middle of supervised and unsupervised learning techniques. This branch of machine learning encompasses several real-world learning issues. This is because semi-supervised uses a lot of unlabeled data and relatively little labeled data, requiring minimal human interaction. It is more desirable to use less labeled datasets because they are more difficult to obtain, costly, and may need access to subject matter experts. Conversely, unlabeled datasets are more accessible and less expensive [55]. In semi-supervised learning, the learning algorithm can be trained using both supervised and unsupervised learning methods.

The input dataset's hidden structures and patterns can be uncovered using unsupervised learning techniques.

On the other hand, supervised learning techniques can be used to make guess predictions on unlabeled data, feed the data back to the learning algorithm as training data, and use the information acquired to make predictions on fresh data sets.

Therefore, we may claim that predictions or hypotheses derived from labeled data are modified or reprioritized using unlabeled data [55].

All semi-supervised learning methods make at least one of the following assumptions in order to utilize the unlabeled training data [55]: manifold, cluster, and smoothness assumptions.

4) Reinforcement

Learning through interaction with the issue environment is known as reinforcement learning.

Instead of being explicitly instructed on what to do, a reinforcement learning agent learns from its own activities.

It chooses what to do now based on current possibilities (exploration) and past experiences (exploitation).

It can therefore be characterized as a process of learning by trial & error.

The reinforcement learning agent receives a signal in the form of a numerical reward value that indicates whether an action was successful.

In order to maximize the numerical reward, the agent seeks to learn how to choose actions [56].

Actions can have an impact on subsequent situations and reward values in addition to the current condition and reward value. Learning agents often have predetermined objectives and are able to perceive the state of their surroundings to some degree.

As a result, they can perform actions that influence the state and move it closer to the objectives.

Based on how each approach acquires knowledge, reinforcement learning differs from supervised learning.

The supervised learning approach uses examples from an outside supervisor. Reinforcement learning, on the other hand, gains

knowledge through direct interactions with the issue environment [5]

5) Deep Learning

This area of machine learning has grown significantly since 2006 and has been used in hundreds of studies since.

Deep learning has been used to a variety of fields, including artificial intelligence and information processing.

In order to create a model that depicts intricate relationships between data, deep learning is a branch of machine learning that relies on algorithms that learn from several levels.

It is called "deep architecture" because there is a hierarchy of features that defines high level characteristics in terms of lower level features. Unsupervised learning representations serve as the foundation for the majority of the models included in this class [57].

In essence, deep learning is the meeting point of signal processing, neural networks, graphical modeling, optimization, artificial intelligence, and pattern recognition.

Deep learning's popularity can be summed up as follows: it greatly increased computer chips' processing power, made it possible to incorporate enormous amounts of training data, and was the driving force behind recent advancements in machine learning in the fields of information and signal processing [57].

IV. ARTIFICIAL INTELLIGENCE CHALLENGES

After applying the SLR, seven new challenges of AI in DT were identified [83]. These new challenges are the "technical blockages", "top management support", "employees' lack of trust for AI and resistance to change", "transparency and explainability", "responsible use of predictive analytics", "data governance", and "intellectual property". The most frequently mentioned challenges were in the ethical category: "high possibility of bias", "data privacy considerations", and "transparency and explainability".

TABLE I. AI CHALLENGES

<i>Challenges of Artificial Intelligence</i>	<i>References</i>
High cost of AI technology	[60, 61, 62, 65, 66, 67]
Data collection & data accessibility challenges	[58, 68, 69]
Poor data quality	[58, 60, 66, 68, 69, 70, 71, 72]
Technical blockages	59, 60, 67, 68, 72
Lack of skills/knowledge	[59, 61, 68, 69, 73, 74, 75]
Top management support	60, 68, 72, 74, 76

Employees' lack of trust in AI & resistance to change	[64, 65, 66, 68, 72, 74, 76, 77, 78]
Over-dependency on technology	63, 76, 77
Lack of empathy	63, 77, 79
High possibility of bias	58, 59, 63, 68, 69, 70, 75, 76, 77, 78, 79, 80, 81, 82
Data privacy considerations	58, 59, 69, 70, 73, 74, 76, 77, 47, 82
Transparency and explainability	[58, 59, 69, 70, 73, 74, 76, 77, 78, 82]
Responsible use of predictive analytics	58, 63, 80, 82, 52
Data governance	59, 68, 80
Intellectual property	77, 82
Cyber security risks	61, 66, 68, 69, 71, 75, 81

V. CONCLUSIONS

Research focusing on Artificial intelligence increasing from last two - three decades in government, industry and academia. Therefore, this article conducted a systematic literature review to explore the concept of AI, CDAC life cycle of AI, its types, AI techniques along with challenges of AI. The outcome of SLR is to assist the researchers or new entrants to understand the concept of artificial intelligence precisely, to grasp how the AI functioning via CDAC life cycle of AI, its techniques and challenges. Based on the outcome of system literature studies, firstly, AI can be defined as systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals. Secondly, The ‘CDAC AI life cycle,’ is presented as the progression of an AI solution through its distinct phases—design, develop, and deploy—and 19 constituent stages from conception to production as applicable to any AI initiative. Thirdly the distinct major AI techniques namely Machine learning, natural language processing (NLP), text and speech synthesis, computer vision, robotics and deep learning. At last the numerous challenges facing by artificial intelligence are technical blockages, top management support, employees lack of trust for AI and resistance to change, transparency and explainability, responsible use of predictive analytics, data governance, and many more. The study has some limitations like the number of databases that were used and also the use of only the research studies written in English language. Researcher and new entrants in the artificial intelligence could use the outcome of this study for better and precisely understanding of AI along with their own study and research.

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