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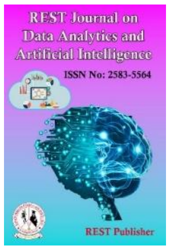

Artificial Intelligence Approaches and Mechanisms for Big Data Analytics: A Systematic Study

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Abstract: *Recent advances in sensor networks and Internet of Things (IoT) technology have led to the collection of large amounts of data. Searching for this much information requires a more efficient and accurate analysis method. Artificial intelligence (AI) techniques such as machine learning and evolutionary algorithms can provide better, faster and more efficient results in big data. Despite this interest, to the best of our knowledge, there has not been a thorough study of the various artificial intelligence techniques for analyzing big data. Most products in the literature focus on the extraordinary ability of intelligence. Recently, challenges such as security, security, integrity, sustainability and utility have emerged during the development of intelligent systems. As the use of smart technology increases, so do new challenges. Obviously, understanding of issues like security will change as we move from narrow AI to super AI. Also, recent advances in human intelligence cannot take place without considering all the problems in creating intelligent machines.*
Keywords: *Big data, Artificial intelligence, Machine learning, Methods, Systematic literature review*.

1. INTRODUCTION

Artificial intelligence (AI) has been widely used in recent years. Many articles in the literature such as [1,2] only focus on the extraordinary ability of intelligence. A few articles (such as those published in [3-7]) focus on cognitive problems. When analyzing intelligence problems, the literature includes security [8], security [9], integrity [10], fire electricity [11] and ethics [12] etc. Many problems have been reported. Some. The widespread use of artificial intelligence presents new challenges. This problem becomes even more complicated when the content of the contest is changed according to the new index described in the next paragraph. From a historical perspective, the evolution of AI-based systems began with narrow artificial intelligence (ANI) that would surpass human performance in every possible way, then general artificial intelligence (AGI) and finally super-intelligent artificial intelligence (ASI). Great [13,14]. All interpretations will be explained in the remainder of this article. Identifying the boundaries between different concepts and new ideas of wisdom is no easy task. In addition, we met with other elements of the field, such as the human level. This article discusses intelligence issues with a particular focus on the HLI. We collected 28 matches from the database, which makes this list unique due to the high competition. The points for each difficulty and their variants are discussed to identify some of the dimensions in ANI, AGI, ASI and HLI. After completing the challenges, some research questions on the development of artificial intelligence address the questions answered to better understand the development of artificial intelligence in the future.

2. EXPLORATORY

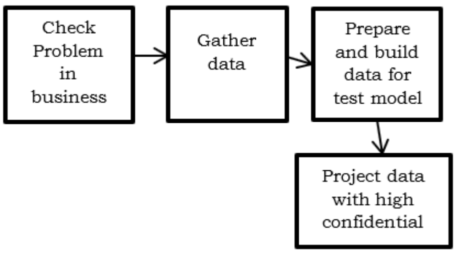

FIGURE 1. Artificial Intelligence Process flow

Since this article focuses on the challenges faced by artificial intelligence by considering different concepts such as ANI, AGI, ASI, and HLI, this section is devoted to speech concepts and their interrelationships. This section first categorizes AI, presents studies of current AI research, and then focuses on human-computer interaction (HLI) because of its importance. According to [15], smart machines are divided into three groups and process flow as explained in figure1.

ANI: This type of intelligence refers to smart machines that perform specific tasks. For example, people working with tasks such as facial recognition and playing games. These agents are designed to perform tasks but cannot be audited and cannot create unknown tasks in self-configuration. We do not want to see self-consciousness in these representatives.

AGI: This concept of AI is not about one particular thing in the minds of all AI experts. Researchers often use AGI for agents whose intelligence is comparable to human agents. AGI can equal HLI [14]. • SPI: In [16], Bostrom proposes three types of intelligence: declarative SSI, total SSI, and qualitative SSI. Speed ASI refers to employees who are faster than humans, Aggregate ASI refers to human-like decision-making abilities, and Quality ASI refers to employees who can do things humans cannot do. Recently, some changes have occurred in the above category. In [17,18] the authors argue that HLI is different from AGI because humans can introduce some assumptions and limitations in the computation of the machine. These considerations and limitations come from the human body of machines. Therefore, AGI may not be able to solve many problems that humans cannot. In other words, people set some implicit upper bounds on systems and reduce overall resources is illustrated in **Figure 2**.

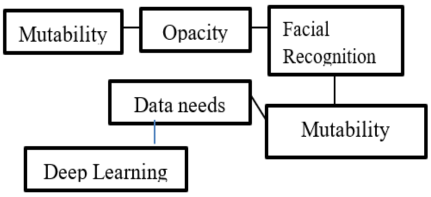

FIGURE 2. Characteristics of AI

On the other hand, authors of some articles such as [18] argue that there is no difference between AGI and ASI when the definition of AGI is not limited to HLI. According to [16,18], if the ability of AGI-based operators is higher than human intelligence and there is no clear definition of ASI ability, there is no need to know the Difference between AGI and ASI. Therefore, in [19] Searle divides intelligence into two categories: weak intelligence and strong intelligence. The remainder of this section is devoted to HLI, as HLI-related issues will become more important in the future.

These codes are divided into (1) Human Intelligence, (2) HLI Development Research, and (3) Competition. The human intelligence segment divides our knowledge into cognitive (eg, accounting is a human cognitive ability), semi-cognitive (eg, psychology is semi-known human abilities), and the last unknown (eg, humans). an idea unknown to people) part. Many studies have been done on the analysis of human intelligence, including mathematics and reasoning. According to [20], many challenges arose during the development of work at the heart of AI-based systems. Therefore, the third part of ***Figure 3*** illustrates the challenges faced by artificial intelligence in the development of HLI. It should be noted that the links given between the challenges and related studies are based on information in the literature. As people's knowledge of AI increases, the cost of research is likely to increase.

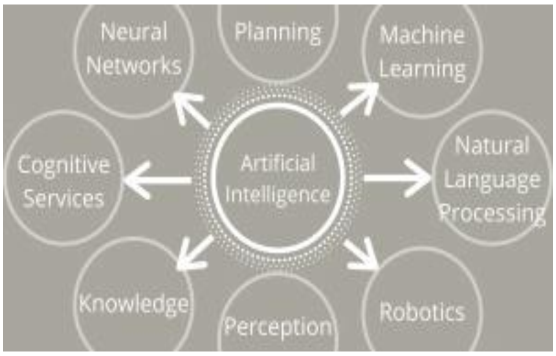

FIGURE 3. AI Challenges

3. DIFFICULTY ANALYSIS

In this section, we focus on the challenges of AI as shown in Table 1. Points should be noted for each difficulty. We mainly focus on R&D related HLI in all competitions. As little is known about the relationship between competition and skill set, we try to find a combination of ANI, AGI and ASI for some challenges. In the remainder of this section, each challenge is explained separately.

Problem analysis and design: Problem analysis and design are important processes to do in the AI workforce. This question plays an important role in establishing HLI-based personnel defined in self-management. The implementation of the above procedure is very difficult in practice due to some of the problems described below. As mentioned earlier, we know that man's awareness of his environment can be viewed in different ways, including known objects, partially known and unknown places. There are many problems that cannot be rendered in a human-friendly format, so there is no clear understanding of how we plan HLI-based agents to solve these problems. For example, [21] shows that some types of problems can be solved without algorithms. Additionally, some human problems, such as the goals of human creation, are unclear, so HLI-based workers will not be able to solve these problems because they follow the thoughts of the same people. This problem is exacerbated when the environment of HLI-based workers is weak and unknown. A search and legal issue should be based on the importance of the HLI based agent. The obligation to identify is discussed in paragraph below.

According to [20], the solution is to map the problem into the search space. In this way, detecting a problem (it can be a single state, multiple states, or sometimes) and then mysteriously construct it is the first step in an AI-based approach. In other words, it is important to gather knowledge and understanding of the nature of the problem and turn it into a problem-solving process. Among the current intelligent people, there is a lot of interest in safety, security, work, etc. The process of creating problems that take into account issues is considered the responsibility of the designers of AI-based agents.

To solve this problem, knowledge workers and those who think about the machine such as Cyc project [22] can make an effort to solve some problems.

Energy Imbibing: Some learning algorithms, including deep learning, use repetitive learning techniques [23]. This method requires a lot of effort. Today, deep learning is used to create HLI-based agents due to their similarity to the human brain and high accuracy in decision making. Deep learning models require GPUs with high computing power. [11] found that these models are very expensive to train and develop due to financial and energy consumption. During the operation of the HLI-based agent, the agent can use the pre-planning method to learn multiple models simultaneously to increase self-awareness. Therefore, advanced computing should support more intelligence. Intermediary AI-based investment in a data-driven approach to learning design.

Data problems in these algorithms can cause many problems. Some of these topics are explained as follows [28-32]:

• Cost is an important information issue. The source of the cost is the collection, preparation and maintenance of data [28].

• The scale of data collected in various systems such as the IoT (Internet of Things) is another data challenge. Such big data gave birth to a new concept called big data. Analyzing big data online with machine learning algorithms is a very challenging task [28-30]. Chapter

Data error (or missing data) is another difficult problem in machine learning algorithms that causes mislead by the algorithm and uncertainty in the analysis process. This problem should be solved at the preprocessing stage. Various methods can be used to solve this problem.

Filling in missing data (completely) with the most frequently found values or developing learning algorithms to estimate missing values are some examples of these methods [32].

Facing challenges in data collection: The data problem in these algorithms causes many problems. Some of these topics are explained as follows [28-32]:

- Cost is an important information issue. The source of the cost is the collection, preparation and maintenance of data [28].
- The scale of data collected in various systems such as the IoT (Internet of Things) is another data challenge. Such big data gave birth to a new concept called big data. Analyzing big data online with machine learning algorithms is a very challenging task [28-30].
- Missing data (or missing data) is another difficult problem in machine learning algorithms, which causes mislearning by algorithms and uncertainty in the data analysis process. This problem should be solved at the preprocessing stage. Various methods can be used to solve this problem. Collecting (filling in) missing data from the most frequently found values or creating learning algorithms to predict missing values are some examples of this model [32].

Athleticism and accuracy: The robustness of the cognitive model refers to the stability of the model's performance after changes in the input data. The reason for this change could be a malicious person, environmental noise, or destruction of other aspects of the AI-based system [8, 31, 32].

For example, during a remote surgery, an HLI representative may detect kidney failure in a patient's vision machine resulting from an unknown accident. The model, which is stronger among many models with similar functions, has more importance in exports. Traditional methods such as repetition and multitasking may not be suitable for smart machines, so the field is still in its infancy.Some studies, such as [33], discuss the discrepancy between the accuracy of the learned model and the strength of this model. It seems that the ideas and concepts of power and belief are still in their infancy, and new things are emerging in the field.

Deceptiveness: The behaviors described above refer to two good human behaviors, but they can appear in intelligent people such as HLI-based agents. While many papers (such as those reported in [34-36]) are devoted to the use of AI-based techniques to detect such behavior in humans, few (eg [37,38]) have mentioned fraud and fraud Analysis in the system. [37,38] examines the role and consequences of fraud in multi-agents. Because HLI-based operators will follow human behavior, they can learn these behaviors from human-generated data. It should be noted that fraud and deception can occur in the behavior of any computer monitor, since the tool focuses only on optimizing certain actions and works on the target first, and the above behavior can have a negative effect on the performance of the target. The above considerations should be considered to develop an HLI-based agent. For more clarity, some explanations are given below. After some models have been built, such as Generative Contention Networks (GAN) [39], machines can create data models. This can be used to create fake news, photos and videos [40].

Security: AI-based systems are widely used to develop security systems such as those presented in [41–43], but from another perspective, it is clear that any software, including training, can be stolen by malicious users [44 - 46]. Security issues are a major concern when developing smart systems. For example, consider the layout of the ant strip where the pheromone update function is hacked to control the search process. Security issues in AI may present some new challenges that cannot be addressed in this document, see [46] for more information. The next article explains the security dimensions, focusing on data-driven machine learning security.

In data-driven machine learning, AI system developers may want to reverse engineer training data or learn how to design models that produce desired outputs [49]. For example, neural networks using untrusted data (synthetic) can be viewed as untrusted learning models in data machine learning. Most AI researchers and developers ignore this problem. Competitor machine learning can be considered the first to solve some of the security problems in machine learning [47]. It is worth noting that as the attack evolves, security mechanism should also evolve accordingly.

Recently, attackers are using artificial intelligence algorithms to plan attacks. Therefore, artificial intelligence-based protection mechanisms should be used to increase the security of AI-based systems [48].

Confidential: Each document contains different types of information that must be protected by certain considerations. [49] identified three data-related factors to demonstrate the characteristics of protection required in the age of wisdom: endurance, repetition, and exhalation. On the other hand, data owner, data manager, and data visualization are three roles that must be defined during the implementation of machine learning. Considering the privacy protection of different roles requires more attention and care from researchers [50]. Federated education is one such effort [50].

This type of learning algorithm trains the algorithm in a wide variety of distributed applications, addressing important issues such as data privacy, data security, and access rights to information. During the design of HLI-based agents, the issue of privacy concerns can be somewhat complex, regardless of whether people accept the privacy of other organizations.

Justice: This occurs when educational standards lead to biased judgments based on certain characteristics such as race, color, gender, religion, ethnicity, citizenship, age, pregnancy, family, disability, veteran and racial background data [51]. Analyzing data on AI integrity can be broken down into three different ways as described below [52]:

- First, the data itself is unfair, making unfair decisions. Therefore, this issue should be addressed at the data level first [53–56] discusses the problems with the data and their biased results. Some suggestions have been made for the preparation of appropriate models of existing documents developed over the last decade. Learn How to Get Flat Patterns [57-60].
- Thirdly, the process and stress method are made to meet the flat limits justified by including them as limitations of the main training objective [61-64].

Understandable in AI: Narrative AI is an emerging field with many applications in many different fields, including healthcare, transportation, and military services [65,66]. In this case, methods and techniques can be used to guide the interpretation of the study model. With such resources, people can avoid prejudice and fair competition etc. can rely on models to make decisions from a variety of perspectives, including [67]. Many learning methods, such as neural networks and deep learning, have extraordinary capabilities, but they invest in non-interpretable signals to complete the task. In many situations, including mission critical, we need to understand the rationale behind the decisions of smart machines, so explaining artificial intelligence can be helpful [67].

In [68,69], recent developments and applications of descriptive learning algorithms in practice are summarized. This challenge is exacerbated when HLI-based personnel performing critical missions in medical, military or other critical situations replace human agents.

Answerability: In the last century, people followed the machine workers. In this context, ethical and legal issues regarding the role of human representatives are clear to all of us. However, this will change when fully autonomous systems are considered. Autonomous machines based on neural networks, genetic algorithms and learning automata pose new problems where humans cannot predict future machine actions [70]. As noted in the next paragraph, this question is more important when creating an HLI.

Dual use is another challenge posed by the abuse of HLI-based systems. Like any other software, these smart machines can be used for good or bad purposes. For example, a malicious broker could use public voice spoofing software to spoof and call bank customers' voices. Further discussion of liability issues can be found in [71].

Manageable: In Manageable theory, the halting problem is the problem of deciding whether to complete an arbitrary computer program given its instructions and inputs. In 1936 Alan Turing proved that there is no general method for solving the halting problem for all possible program inputs [72,73]. Therefore, there is no general procedure for programming agent x. Theoretically, some of the AI management problems can be reduced to a simple problem but are not considered solvable problems [73]. If we accept that this problem is solvable, we must accept that many other problems, such as the stopping problem, are also solvable. In the age of super intelligence, agents will be difficult to control by humans [74,75]. Note that management as its content has many dimensions, and several articles (eg [76]) focus on this topic in some areas, such as security. There are four types of governance in [76]: explicit, implicit, delegated, and compliant. It turns out that this problem cannot be considered for security concerns and may be exacerbated by increasing the autonomy of AI-based robots.

Persistence: A major unresolved challenge is that the decisions of AI-based agents can be predicted in any situation [77-79]. The direct benefit of this challenge is that we can discover whether smart workers are manageable and whether the smart people of the future are secure (or trustworthy). Due to the nature of the estimation challenge, solving this challenge is not trivial. Next, we introduce some of them. It is worth noting that due to the nature of these types, unpredictability can be seen in the behavior of employees using reinforcement learning algorithms.

In [80], some problems with the estimation of AI-based operators are noted. Bad behavior in math and physics seems to play an important role in this problem. In other words, there are some similarities between stress in math, physics and AI, so in some cases AI decisions cannot be seen. Other issues such as uncertainty and inconsistency can make AI-based systems unpredictable. Failure in the HLI-based broker can cause many issues such as security, trust, responsibility, and fairness.

Pursuit of knowledge: During the lifecycle of AI-based systems, the accuracy of the learning model goes down because of changes in the data and environment of the model. Therefore, the learning process should be changed using new methods to support continual and lifelong learning. On the other hand, in real-world applications, a massive amount of data is produced via the Internet of Things (IoT) and embedded sensors in a real-time manner. Hence, new systems' algorithms should be considered a stream of data and continuous learning.

Memory: Memory is an essential part of any AI-based system. Limited memory-based AI systems are one of the most common and widely used types of artificial intelligence [81]. In this mode, historical analysis is used to estimate some parameters related to changes in data. In this method, some data-driven and statistical analysis is used to extract information from the data. This approach is not new to AI and is used by data, storage, power consumption and learning capability as described below.

In general, learning can be improved with more information. As the amount of data collected by AI-based systems increases, efficient algorithms are required for data analysis and decision making. With the rise of information, the technology behind storage and computing may change in the future. Information can be stored in short-term or long-term memory, causing problems in many different areas such as reading, counting and writing. In [82], an artificial intelligence-based method is proposed to solve this problem.

Acceptable and pertaining: Colloquially, both morality and ethics mean "right" and "wrong". Sometimes these terms are used interchangeably, but they mean many things. Ethics refers to rules issued by outside organizations, such as workplace rules or religious norms. Morality refers to personal principles about right and wrong. Due to the great overlap between the mentioned concepts, we will discuss the shared components in the remainder of this section, focusing on AI and HLI. Ethics is a complex concept in artificial intelligence due to its diversity and different actors. Ethics is considered a moral code that guides behavior. From an ethical point of view noted in the learning process to protect the identity of data [83].

Argumentation: The main purpose of intelligence research is to understand intelligence. Organizational values theory has long been seen as a key player in defining intelligence. Computational analysis plays an important role in distributed machine learning, multi-agent systems, game theory and AGI [88-90]. In [91] rationality is defined in four categories as follows:

- Perfect rationality: An agent with such rationality can create the best behavior based on the information he has.
- Computational Rationality: An agent with such rationality can calculate the best decision based on the information available in the first place.
- Meta-level rationality: An agent with this logic can choose the best aggregate combination for action. In this process, the following parameters are the calculations to be selected.
- Bounded Rationality: An agent with this rationality can act on available information and calculated information.

Progression: Darwinian evolution, including "survival of the fittest", has been published in the literature to describe AI-based models. In this way, AI models can improve generational changes without human assistance. This approach is not perfect, and many issues need to be resolved to provide a self-evolving AI model.

• According to the theory, the structure of existing genes and chromosomes and the evolutionary process are not the same as the evolutionary process that takes place in nature. It seems that computer bugs and bugs using some programming like quinn codes and polymorphic models are more pioneering than existing changes that can be found in archives like GitHub.

In [92], a self-replicating neural network is proposed that can be used for evolutionary strategies. • According to evolutionary computation theory, the ideas behind genetic and memetic computation change over time to better simulate phenomena that occur in nature. There are many variations of these algorithms, such as different chromosomes, different crossings, and complex mutations. It should be noted that many existing evolutionary algorithms rely on very readily available processes occurring in nature [93].

Reliability: According to [94], the reliability of AI will promote social, economic and sustainable development by making the most of AI for people, organizations and community power. Five principles in [94]; Courtesy, non-violence, freedom, justice, and interpretation are all covered here. The field is very interdisciplinary and dynamic and covers many topics in psychology, sociology, economics, management and computer science. As stated in [12], social trust has a strong relationship with morality. In [95], justice, interpretation, responsibility, and trust were reported as trust-related concepts.

4. IMPORTANCE OF COMPLEX CONCEPTS

Reaching the Dark Side: Many AI researchers focus only on solving specific problems against a background of fixed requirements, and more in steady state. These assumptions can lead to bad situations in practice because smart machines will be used in many products and industries with different requirements. For example, for static data, the main points of fair competition are taken into account. Today this thinking has completely changed and we need to adapt the curriculum to some areas where we are strong. Therefore, a robust algorithm for fair decision making may not be viable [51]. In [51], a method is proposed for fairness-conscious classification that preserves the performance of flows with low discrimination scores. Creating an HLI representation that takes reliability into account is the ultimate goal of cognitive science.

Evolution and Transformation of Challenges: Tracking the truth about the development of AI-based systems is an evolving challenge. This problem is exacerbated when difficulties and associated problems appear after industrial-level problems arise. Changes to some challenges are described below:

• Changes to data challenges: We have limited data with the development of data-driven machine learning algorithms.

We now have big data due to the use of cloud computing. In the future, due to the use of artificial intelligence-based data generation such as generative competitor networks (GANs), we will need strategies to distinguish the true response and relevant information in the world from other types of information in many documents [96,97] .

• Evolution of Robustness and Security Challenges: If the noise of the input data is synthetic and tuned to abnormally change the behavior of the model, we will encounter another challenge in the Security Challenges reviewed, called competitor security. Due to the large number of attackers, robustness is generally quickly linked to security [31].

• The Evolution of the Energy Consumption Challenge: It was previously said that energy consumption is a major problem in the life of AI-based systems.

This competition will lead to other problems such as carbon emissions, environmental pollution and global warming [98].

• Evolution of Complexity Challenges: Very complex systems can make AI-based systems unreliable, unreliable, irresponsible and impossible to develop. For example, models with many parameters and complex methods of correcting them can cause reproducibility problems as described in [99].

5. CONCLUSION

This article examines these intelligence issues with a particular focus on the HLI. It should be noted that the competition is not similar in popularity. In other words, some challenges (like stability and integrity) are more popular than others (like strength and complexity). Therefore, each challenge is briefly explained to understand the challenge. Also, the link and connection between competition and its changes are examined. Due to its popularity in terms of intelligence, we have left behind some well-known challenges such as the curse of greatness. Clearly, in the transition from ANI to ASI, all the challenges will be about the new as we see more about the environment as we interact with smart machines. We try to resolve this issue in the Discussion section. Some of the challenges posed by monopoly and unemployment in the age of artificial intelligence are beyond the scope of this article, as the topic of this article is often computer science. These issues can be evaluated in future studies.

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