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A Critical Analysis on AI Techniques and Applications in Smart Systems

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Abstract. AI remains one of the key predicates of the Fourth Industrial Revolution in terms of automation, intelligent computing and creation of smart systems. This paper critically analyzes AI techniques and their applications across various fields, including healthcare, cybersecurity, smart cities, finance, and agriculture. It explores the role of AI in decision support systems, context-aware computing, and intelligent automation. The paper discusses key AI methodologies such as machine learning, deep learning, data mining, fuzzy logic, and knowledge representation, highlighting their contributions to smart system development. Additionally, the study identifies challenges in AI deployment, such as data privacy concerns, algorithmic biases, and scalability issues, while proposing future research directions to enhance AI-driven solutions. The findings emphasize AI's transformative potential and its impact on Industry 4.0, fostering innovation, efficiency, and sustainability.

Keywords: Industrial Revolution; Artificial Intelligence; Machine Learning; Deep Learning; Data Analytics; Intelligent Systems.

1. Introduction

The Fourth Industrial Revolution, also called Industry 4.0 or 4IR is the new lifestyle of today's world [1]. It envisages the rapid change in technology trends in various domains such as industries, processes and social patterns formed due to advanced connectivity and smart automation. Its implementation causes remarkable revolution in all domains. The Fourth Industrial Revolution, characterized by rapid advancements in automation, intelligent systems, and smart computing, underscores the transformative potential of Artificial Intelligence (AI). Industry 4.0 is transforming the world by integrating AI-powered capabilities into everyday processes, enhancing human potential, driving innovation, and addressing complex global concerns [2]. It empowers industries to operate with greater precision, adaptability, and intelligence, paving the way for a more sustainable and interconnected future. The three main pillars of automation, intelligent computing, and smart computing are at the foundation of the Fourth Industrial Revolution. Every one of these technologies is essential for promoting creativity, effectiveness, and game-changing applications in a variety of sectors [1].

1. Automation: It refers to automating machines to perform operations without human collaboration. It is one of the main trends that includes a vast number of technologies that minimizes human involvement in its performance. In many cases a program, a script or batch processing to minimise or eliminate the need for individuals to complete repetitive tasks. Automated decision-making goes a step beyond the use of computational analytics to uncover fertile insights, applying AI-based automation instead. In customer service, for instance, virtual assistants cut on expenditure for instance beneficial to both customers and human agents providing them with power, which is more, with particular importance in creating a better customer experience. Artificial intelligence when it comes to technology the viewpoint is that there is a possibility to automatize nearly everything industry and every person on the planet since the beginning of the world.

2. Intelligent Computing: It is the extraction of useful information from data. It is also known as computational intelligence, and it refers to a computer or system ability. In generic terms, it is referred to as finding intelligence or useful information out of data or experimental observation, or to master a given job or task. Intelligent computing methodologies encompass information processing, data mining and knowledge discovery, machine learning and pattern recognition, signal processing, natural language processing, fuzzy systems, knowledge representation and reasoning. Transportation, industry, health, agriculture, business, finance, security, and other domains might be supported by intelligent systems.
3. Smart Computing: In smart computing, the word smart is managed as the capacity to self-monitor, analyze, and report technology, while the word computing refers to computational analysis. It is, thus, considered as the second generation of computing that is employed in order create something with a measure of consciousness, this is something that can capture the activities occurring in its context, process these activities by making them into data then perform some analysis on them and come up with the best course of action while at the same time possibly predicting other emergent vices and virtues. In general, it aims at establishing a smarter system by capturing, processing and presenting the data more quickly and intelligently through AI modeling forms a very important component of the system wisdom and decision making process.

AI-based modeling involves embedding human-like cognitive abilities into systems to solve real-world problems with precision and efficiency. This paper reviews contemporary AI techniques, their applications, and the challenges encountered in building scalable and effective AI models. The focus is to provide a foundational understanding for researchers and practitioners aiming to leverage AI in diverse fields.

The paper provides a full understanding of AI and its role in automation. It starts with Industry 4.0 and then explores Artificial Intelligence and its types. The paper then digs into the literature review of AI in the construction of smart systems, demonstrating its transformational potential across industries. Table 1 presents a comprehensive review of important data, providing insights into the efficacy of AI in smart systems. Following this, the discussion section critically assesses the findings, taking into account both existing issues and potential. The future scope part discusses prospective developments in AI and smart systems, while the conclusion highlights significant issues and underlines the role of AI in creating the future of Industry 4.0.

1.1. Industry 4.0

The current industrial world is known as Industry 4.0 mainly due to installation of Artificial Intelligence guided technology in industries. Industry 4.0 came into being after Industrial Revolution 3.0, when the focus shifted to automate the machines and processes using IoT, cloud computing and smart decision making with smart factory deployment. This Industrial Revolution revolutionizes machines to use AI algorithms to interpret data and make smart decisions using them.

Artificial Intelligence – AI along with other smart technologies has the potential to produce tremendous growth in the economy of manufacture, transport, commerce etc. Hence, the role of AI-based modeling in the Fourth Industrial Revolution is focused in this paper.

AI is a computer science field that makes machines smart enough to perform in a way similar to humans. It benefits humans by carrying out tasks in less time and managing a large network of individuals in businesses, states and countries. AI's priority is to revolutionize computers and machines in such a way that it can perform human-like cognitive functions for instance decision-making, problem-solving. Every industry, business can prosper faster and precisely by implementing AI based modeling.

AI has played a major role in revolutionizing the industry sector by automating machines and making them intelligent and smart enough to work efficiently, hence, building 4IR. On the other hand, AI based modeling is a complex task because of dynamic real-time scenarios and variety in data. Therefore, a number of AI types are considered.

1. Analytical AI:

It promotes data driven decision making by understanding the given data and producing recommendations based on it.

2. Functional AI:

It differs from analytical AI as it aids decision making process and takes actions after extracting insights from data.

3. Interactive AI:

It boosts business growth by automating the communication with users such as providing customer care through chat bots or smart personal assistants.

4. Textual AI:

It helps with text recognition, processing and analytics, thereby providing speech-to-text translation, and content generation features.

5. Visual AI:

It provides machine generated virtual reality or augmented reality.

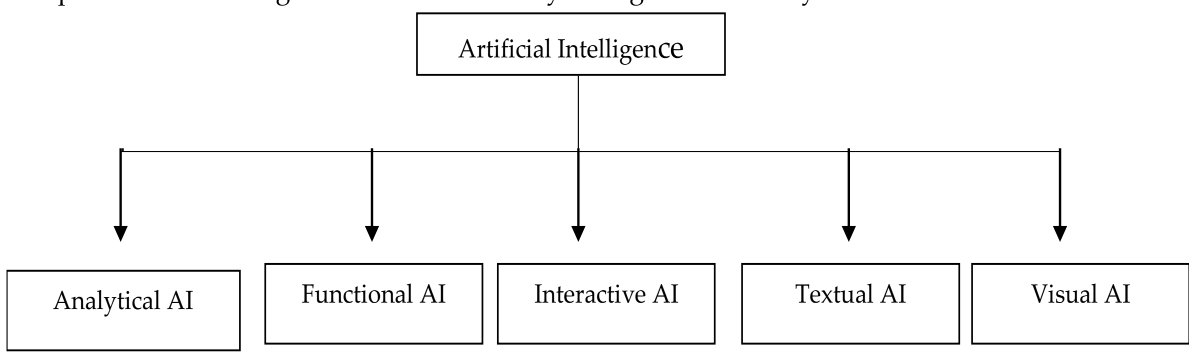

Figure 1. Types of Artificial Intelligence [3]

The division of AI techniques into ten categories in the paper provides a bird's eye view of the diverse potential of artificial intelligence as follows. Therefore, by supplementing the theoretical analysis of each approach with examples of its practical application, the paper enhances its educational value.

1. Machine Learning (ML)
2. Deep Learning and Neural Networks
3. Data Mining, Knowledge Discovery and Advanced Analytics
4. Rule based modeling and Decision making
5. Fuzzy logic based method
6. Knowledge representation, uncertainty reasoning and expert system modeling
7. Case based reasoning
8. Text Mining and Natural Language Processing
9. Visual Analytics, Computer Vision and Pattern Recognition
10. Hybridization, Searching and Pattern Recognition

2. Types of AI

AI is a broader domain of computer science that understands data and generates patterns to carry out jobs such as solving complex problems, having cognitive intellectual approach.

2.1. Machine Learning (ML)

Machine Learning is the study of algorithms that are implemented on machines to automate analytical AI based model building [4]. Machine Learning models are made up of rules and regulations, policies and procedures or transfer functions that help to predict behaviors and data patterns [5]. Another name for machine learning is Predictive Analytics as it can predict some of the future trends by using a given dataset. Following are some types of ML techniques used for modeling in any specific domain:

2.1.1. Supervised Learning:

It follows a task-driven strategy to accomplish goals from data. It uses labeled data input for training algorithms for classification of data. Its main two functions are classification and regression analysis. For example, Support vector machines (SVM), K-nearest neighbors [6], CART, BehavDT [7], Support vector regression , Random Forest are used to carry out supervised learning tasks. The use of each function depends on the type of given data in a specific scope. For example, classification can be used to detect cyberattacks whereas regression can be used to assess and manage the loss due to cyberattack.

2.1.2. Unsupervised Learning:

It follows a data-driven strategy that uses unlabeled data to discover structures, knowledge and patterns. Its main functions are anomaly detection, visualization, finding association rules, clustering and dimensionality reduction. It uses a number of clustering algorithms i.e. K-means [8], DBSCAN [9], hierarchical clustering, single linkage [10] or complete linkage [11], BOTS [12], association learning algorithms such as AIS[13], Apriori [14], Apriori-TID and Apriori-Hybrid [14] and extraction and feature collection techniques such as Pearson Correlation [4]. This type of ML helps to grow business by identifying target customer group and segmenting them accordingly.

2.1.3. Semi-supervised Learning:

It is a hybrid of supervised and unsupervised learning techniques as it uses both labeled and unlabeled data for training a model. It is useful for a model's performance when the data labeling is automatically completed without human collaboration such as internet content classification.

2.1.4. Reinforcement Learning:

Another kind of ML technique is reinforcement learning, which penalizes undesirable actions while rewarding positive ones. A reinforcement learning agent can perceive and comprehend its environment, act, and learn by making mistakes like an environment-driven approach, where decisions are determined using a reward function and the environment is usually represented as a Markov decision process [15]. The most popular reinforcement learning algorithms are Deep Q Networks, Q-learning, and Monte Carlo learning [16]. Reinforcement learning may be applied to autonomous driving tasks such as trajectory optimization, motion planning, dynamic pathing, and scenario-based learning rules for highways.

2.2. Neural Networks and Deep Learning

A number of applications of ML models are discussed as Blumenstock et al. [17] offer a machine learning approach to ensuring that COVID-19 aid reaches those who require it most. In the field of cybersecurity, Sarker et al. [18, 19] point out a variety of cyber abnormalities and assaults that can be identified by machine learning techniques. A machine learning-based approach to creating an efficient smart parking charging infrastructure for smart city settings is described by Saharan et al. [20]. The DL [21] is an Artificial Intelligence method that implements Artificial Neural Networks (ANN). It works with multiple layers of input and output data that forms the basis for deep neural networks. According to [22], Deep Learning has 3 basic types:

2.2.1. Discriminative Learning

This type of DL provides a discriminative function i.e. pattern categorization discrimination. The posterior distribution of classes are conditioned on observable data and then it is categorized [23]. Convolutional neural networks (CNN or ConvNet) [24] and Recurrent Neural Networks (RNN) [25] are used to develop discriminative deep architectures to provide solutions for real time problems.

2.2.2. Generative Learning

It identifies high order correlation features and qualities for pattern analysis. It uses these identified features for joint statistical distributions of data and their respective classes [23]. This approach of deep learning does not focus on particular supervisory data such as target class labels. It is widely applicable for unsupervised learning such as data generation and representation and feature learning[23, 26]. Moreover, it can be used for the preprocessing step of supervised learning that determines the accuracy of a discriminative model. To solve real-time problems, Autoencoder (AE) [21] and Self-Organizing Map (SOM) [27] can be used.

2.2.3. Deep networks for hybrid learning

Hybrid deep learning models are formed on the basis of a pattern to train both discriminative models and deep generative models as well. The basic model in a hybrid DL model can be either a discriminative model or a generative model or a combination of both shadowed by a non DL classifier.

2.2.4. Applications of DL

Aslan et al. [28] proposed a CNN-based transfer learning method for COVID19 virus detection. Islam et al. [29] suggested a shared deep CNN-LSTM network for the prediction of Corona virus using X-ray. Kim et al. [30] detected zero-day malware using transferable generative adversarial networks built on deep autoencoders. Anuradha et al. [31] used a reinforcement LSTM model to develop a deep CNN-based stock trend estimation .Wang et al. [32] provided a deep learning based real-time solution for collision problem in transportation systems. Dhyani et al. [5] implemented deep learning with Bidirectional RNN and attention model to generate an intelligent Chatbot.

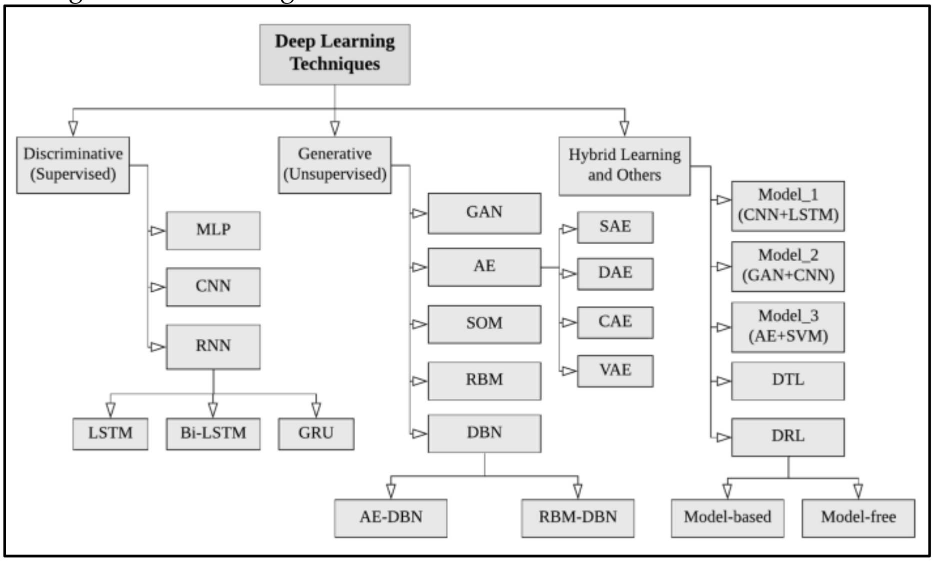

Figure 2. A taxonomy of Deep Learning [22]

2.3. Data Mining, Knowledge Discovery and Advanced Analytics

Han et al. [33] suggested using “knowledge mining from data” as an alternative to data mining. Data Mining, also referred to as Data Science [34], is defined as the process of gleaning knowledge and patterns from massive amounts of data [33]. It is a concept that combines data analytics, data statistics, and associated techniques for data analysis. In the data analytics field [34], key questions like "What happened?" "Why did it happen?" "What will happen in the future?" and "What action should be taken?" are frequently asked and crucial.

There are four analytics types that can be utilized to create the corresponding data-driven models based on such key questions:

Descriptive analytics: It analyzes past data to have a deeper comprehension of how a company has evolved. Therefore, descriptive analytics provides an answer to the question, "What happened in the past?" by summarizing historical data for instance, operations statistics, marketing strategies and sales, social media usage, etc.

Diagnostic analytics : This kind of advanced analytics looks at information or material to determine "why did it happen?" The goal of diagnostic analytics is to help identify the underlying root cause of the issue.

Predictive analytics : It investigates the data to determine "what will happen in the future?" Hence, its main goal is to find a highly confident answer to this question.

Prescriptive analytics: It concentrates on providing data-driven advice on the best course of action to maximize overall results and profitability, addressing the query, "What should be done?

2.3.1. Applications

A data mining technique to maximize the competitive advantage on e-business websites is offered by Alazab et al. [35] and Afzaliseresht et al. [36] proposed human-centered data mining for cyber threat information from logs to stories. An automated diagnostic analytics workflow for the identification of production events, application to mature gas fields, has been reported by Poort et al.[37]. Using machine learning algorithms and scheduling rules, Srinivas et al. [38] offer a prescriptive analytics approach for improving outpatient appointment systems.

Therefore, data mining and analytics, using the insights gleaned from the data, can be extremely important in the development of AI models.

2.4. Rule –Based Modeling and Decision Making

A rule-based system stores and transforms the knowledge to comprehend information in a significant manner. A rule base is has a list of rules written in the form of IF-THEN statements of the form i.e.

IF < antecedent > THEN < consequent >

An expert system model based on IF-THEN rule has the ability to make decisions just like a human being's cognitive thinking [39]. The rule-based models have significant applications in real life to solve real-time problems, the main reason behind it is the rules that are easy to understand and easy to represent relevant knowledge. Another reason is that rule based models have the potential to improve according to the requirements by creating, removing, and modifying rules based on domain expert information or based on recent trends [39]. Earlier, "rule-based system" referred to systems that used rule sets created by humans or manmade.

2.4.1. Applications

Rule-based machine learning methodologies prove to be very useful in automating machines and making them intelligent by classifying and associating rule learning techniques[39]. BehavDT [7], IntrudTree [40], Repeated Incremental Pruning to Produce Error Reduction (RIPPER) [41], etc. are some classification techniques that exist with the ability of rule generation.

Association rules are based on support and confidence values that are built from searching common IF-THEN pattern data. A rule-based model can be developed by using a given data set such as AIS [13], Apriori [14], ABC-RuleMiner [42]. Sarker et al. [42] delivered a rule-based machine learning strategy for context-aware intelligent and adaptive mobile services. Borah et al. [43] employed dynamic rare association rule mining to discover risk factors for critical illnesses. Bhavithra et al. [44] developed a personalized web page experience using case based clustering and weighted association rule. A risk prediction and early warning system for air traffic controllers' dangerous activities was reported by Xu et al. [45] using random forest and association rule mining. Therefore, it can be concluded that rule-based modeling can play a major role in the development of AI models and smart decision-making in a diversity of application domains to address real-time issues.

2.5. Fuzzy Logic based Approach

Fuzzy logic is a definite logic of imprecision and approximate reasoning. This is an obvious extension of standard logic where the degree of truth of a concept—also referred to as membership value or degree of membership—can be within 0.0 and 1.0 range. Only concepts that are true (degree of truth 1.0) or untrue (degree of truth 0.0) are covered by standard logic. Conversely, fuzzy logic deals with the idea of partial truth, where the truth value can be anywhere between 0.9 and 0.5, which are totally true and completely untrue, respectively. Fuzzy logic-based models identify, describe, modify, understand, and apply vague and uncertain facts and information.

Fuzzy logic has following 4 parts:

1. Fuzzification:

   It converts the input into fuzzy sets. For example, it transforms numbers into fuzzy sets.

2. Knowledge base:

   It includes the set of guidelines and IF-THEN requirements that the experts provide to control the system of decision-making based on linguistic data.

3. Inference Engine:

   It evaluates the rules that should be invoked based on the input field and calculates the matching degree of the current fuzzy input with respect to each rule. After then, the control actions are created by combining the Fred rules.

4. Defuzzification

   It converts the fuzzy sets produced by the inference engine into numbers.

The fuzzy logic technique is chosen over ML models when the differentiating features are ambiguously defined. The fuzzy logic technique is recommended when distinguishing qualities are ill-defined and depend on human knowledge and expertise, even though ML models may differentiate between at least two object classes depending on their capacity to learn from data. As a result, the system can process any kind of input data, including limited data and data that is loud, distorted, or imprecise. Since it makes use of data collected in environments with such characteristics, it is an appropriate tactic to employ in situations involving actual, continuous-valued elements [47].

2.5.1. Applications of Fuzzy Logic

Numerous fields employ models based on fuzzy logic to address issues. For instance, Reddy et al. [38] employ a fuzzy logic classifier to diagnose heart illness, and an adaptive genetic algorithm is used to optimize the rules that are obtained from fuzzy classifiers. A fuzzy logic-based smart irrigation system that uses the Internet of Things and sends out recurring acknowledgement alerts on task status such soil temperature and humidity is described by Krishnan et al. [48]. A fuzzy logic-based network anomaly detection technique is described by Hamamoto et al. [47] to determine whether a certain instance is unusual. A fuzzy weighted association rule mining technique was presented by Kang et al. [49] for creating a customer satisfaction product form. All things considered, we can conclude that fuzzy logic may draw logical conclusions in an environment of ambiguity, imprecision, and incomplete data; as a result, it may be helpful in these situations while developing a model.

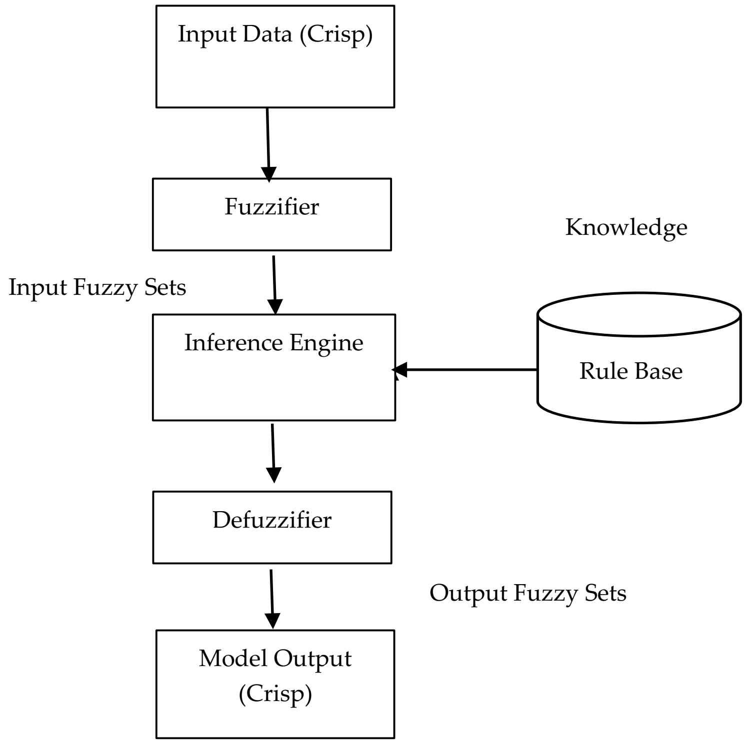

Figure 3. An architecture of Fuzzy Logic based system [46]

2.6. Knowledge Representation, Uncertainty Reasoning, and Expert System Modeling

One of the most promising areas of artificial intelligence is knowledge representation, which is the study of how an intelligent agent's principles, objectives, and judgments could possibly be effectively presented for automated reasoning. The process of drawing conclusions, formulating predictions, or creating explanations using what is already known is known as reasoning. Descriptive knowledge, structural knowledge, procedural knowledge, meta-knowledge, and heuristic knowledge are only a few of the many forms of knowledge that can be applied in many fields[42]. Knowledge representation enables an intelligent computer to operate intelligently like a human by learning from its experiences and knowledge, going beyond simply storing facts in a database. Therefore, an efficient knowledge representation technique is necessary for creating an intelligent system. A knowledge-based conceptual model can be developed using a variety of knowledge representation techniques, such as production rules, logical, semantic network, and frame [50]. The possible knowledge representation techniques that take into consideration real-world problems are compiled as follows:

Ontology is generally defined as "a formal method to define the semantics of knowledge and data and an explicit specification of conceptualization" [51]. A formal representation of an ontology is

O = C, R, I, H, A

where C = C1, C2, …, Cn represents a set of concepts and R = R1, R2, …, Rm indicates a set of relations defined over the concepts. Here, I refer to a collection of concept instances, H for a Directed Acyclic Graph (DAG) that is determined by the subsumption connection between concepts, and A for a collection of axioms that impose extra restrictions on the ontology. For processing tasks or processes, ontology-based knowledge representation and reasoning techniques offer advanced environmental knowledge. Ontologies facilitate concise communication between humans and machines by specifying shared and common domain theories that provide semantic knowledge for a specific domain. Ontology-based techniques like classification, association rule mining, clustering, link discovery, etc., might be very important in the field of semantic data mining in order to create automated systems.

The rule-based, in other words, "IF < condition > THEN < action >," usually comprises combinations of the condition and matching action [39]. An agent first verifies the condition, and if it is met, the associated rule is activated. The main advantage of a rule-based system such as this one is that the "condition" component can decide which rule to apply in a certain situation. The implementation of the problem's remedies, however, falls under the purview of the "action" section. Additionally, adding, removing, or updating rules as needed is simple with a rule-based system.

Uncertainty and probabilistic reasoning: A way of representing information known as probabilistic reasoning uses the idea of probability to denote knowledge uncertainty and combines probability theory and logic to handle that uncertainty [52]. Probability can be defined as the likelihood that an uncertain event will occur and is the numerical representation of the possibility of an event happening. Bayesian belief networks, fuzzy logic, probabilistic models, and other techniques can be used to address uncertainty in a model.

These knowledge representations are essential to a knowledge-based system, like an expert system for decision-making. The expert system is composed of two subsystems: the knowledge base and the inference engine where the inference engine searches for knowledge-based data and connections before offering conclusions, forecasts, and suggestions.

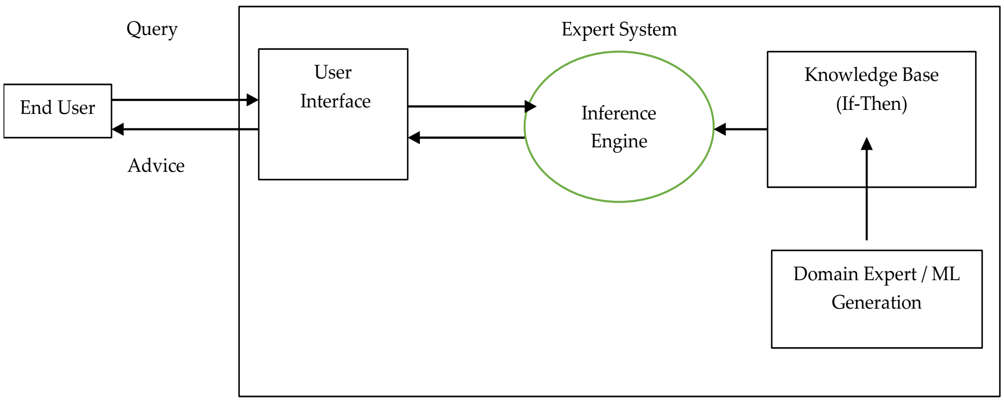

Figure 4. An architecture of Expert Systems [46]

2.6.1. Applications

Ontology-driven AI and access control systems for smart fisheries are presented by Chukkapalli et al. [53]. Improved security-aware methods and ontology control for data access in cloud computing are presented by Kiran et al. [54]. A conceptual ontology and computer intelligence warning system for managing cyber-security vulnerabilities is presented by Syed et al.[55]. Talib et al. [56] have proposed an implementation of an ontology-based cyber security policy in Saudi Arabia. Sarker et al. [57] have recently investigated expert system simulation for customized mobile app decision-making. Therefore, to create AI models and make intelligent decisions across a range of application domains to address real-world problems, knowledge representation and modeling are crucial.

2.7. Case-Based Reasoning

An artificial intelligence paradigm known as case-based reasoning (CBR) portrays reasoning as mostly memory-based. The "smart" reuse of knowledge from cases—problems that have already been resolved—and its adaptation to new, unresolved issues are the focus of CBR. The inference is a method for addressing problems that is based on how closely the current circumstance resembles previously resolved issues that have been documented in a repository. This approach assumes that solutions to similar situations will be similar as well.

Case-based reasoning uses previously stored 'cases' to tailor answers to new issues and requirements. Medical education uses case histories and therapies to help diagnose and treat new patients. Figure 10 illustrates the general architecture of case-based reasoning. CBR research refers to the CBR process as a model of human cognition and an approach for creating intelligent systems.

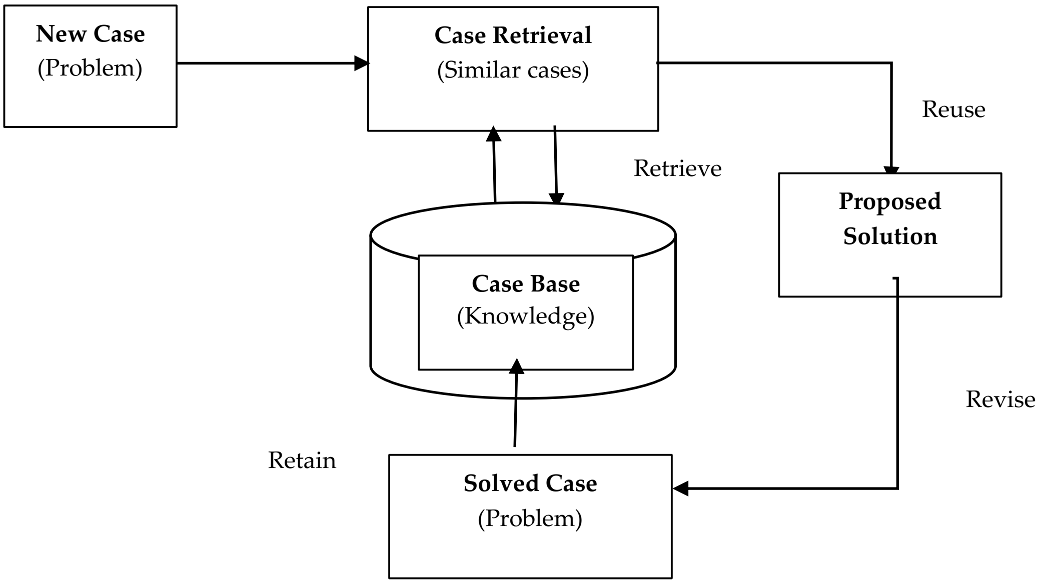

Figure 5. An architecture of Case based Reasoning [46]

2.7.1. Applications of Case based Reasoning

Lamy et al. [58] propose a visual case-based reasoning technique for explaining artificial intelligence in breast cancer. Gonzalez et al. [59] propose a case-based reasoning-based energy optimization approach. Khosravani et al. [60] propose a case-based reasoning approach for fault detection in dripper manufacturing. Corrales et al. [61] developed a case-based reasoning framework to offer data cleaning algorithms for classification and regression challenges. CBR becomes more intelligent as the number of saved examples increases, making it beneficial for creating models in certain settings. As the time required to discover and handle relevant cases increases, the system's efficiency decreases.

2.8. Text Mining and NLP

Text mining [62], known as text data mining, extracts relevant information from many written resources, including web apps, books, emails, documents, feedback, and publications. It is similar to text analytics. Text analysis includes information retrieval, lexical analysis for frequency of word distributions, pattern recognition, annotation, extraction, link and analysis of associations, visualization, and predictive analytics. Text mining does this through a range of analytical methods, including natural language processing (NLP). Natural language processing (NLP) is a text analysis technology that allows computers to understand human speech. NLP tasks include speech recognition, word segmentation, stemming, parsing, word sense disambiguation, identification of named entities, sentiment analysis, topic segmentation, and natural language generation [63]. NLP techniques have real-world applications, including fake news identification, spam detection, machine translation, question answering, social media sentiment analysis, text summarization, virtual agents, and chatbots.

2.8.1. Applications of NLP

NLP currently combines computational linguistics with statistical, machine learning, and deep learning models, even though many language-processing systems were initially constructed using symbolic techniques, such as manually writing a set of rules and consulting a dictionary [4, 22]. When combined, these technologies enable computers to process human language as text or audio data and fully understand its meaning, including the sentiment and intent of the writer or speaker. Numerous projects have been completed in this field. For instance, Phan et al. [64] suggest a technique for enhancing the sentiment analysis performance of tweets with a fuzzy sentiment by utilizing the feature ensemble model. The sentiment analysis of product reviews is provided by Onan et al. [65] using deep neural networks and weighted word embeddings. Sentiment evaluation of tweets for determining event criticality and security is presented by Subramaniyaswamy et al. [66]. Learning techniques, rather than static analysis, are more effective for automating and enhancing textual modeling or NLP systems. Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), enable systems to learn and extract meaning from enormous quantities of unstructured, unlabeled text and speech input [4]. Deep learning techniques, such as generative and discriminative models, can be used to create powerful textual or NLP models based on their data learning capabilities, as discussed in Sarker et al. 's paper [22]. This could be a promising research direction in the field. Combining ML and DL techniques with natural language processing allows computers to evaluate and infer meaning from human voice or text, potentially valuable for developing textual AI models.

2.9. Visual Analytics, Computer Vision and Pattern Recognition

Computer vision [67] is a type of artificial intelligence that extracts information from digital photos, movies, and other visual inputs and generates recommendations using it. An engineering goal is to understand and automate activities that the human visual system can perform. Consequently, this corresponds to the automated process of extracting, analyzing, and comprehending pertinent data from a single image or a collection of photos. The technology involves developing a theoretical and technical framework for autonomous visual understanding through pixel-level image processing. Computer vision and visual analytics often deals with issues including object classification or recognition, detection, tracking, image restoration, feature matching, image segmentation, scene reconstruction, video motion analysis. The automated identification of patterns and regularities in data, or pattern recognition, is the foundation of modern computer vision systems. Frequently, pattern recognition involves dividing (unsupervised learning) and classifying (supervised learning) patterns [4].

2.9.1. Applications

Convolutional neural networks (CNN or ConvNet)[22, 24] have shown a great potential in computer vision applications, such as scene analysis, object detection, and classification. These algorithms are often trained using large datasets of labeled training data (thousands or millions). However, limited data availability hinders the development of apps. Supervised learning requires labeled data, despite the ability to rapidly collect large amounts of data. Data labeling is time-consuming and expensive. Significant progress has been made in this area. Elakkiya et al. [68] created a cervical cancer diagnosis healthcare system using hybrid object detection adversarial networks. Harrou et al. [69] propose a vision-based system for detecting human falls in residential settings. Pan et al. [70] used deep learning to recognize and classify navigation marks. In such visual analytics, learning methods are usually more efficient in terms of automation and intelligence than static analysis. As mentioned in Sarker et al. [22],in addition to standard ML algorithms [4], generative and discriminative models are two DL techniques that can be used to create powerful visual models based on their learning capabilities from data. This could also be a significant research direction in the field. Therefore, in the current era of the Fourth Industrial Revolution, or Industry 4.0, it is important to develop efficient visual AI models in a variety of application domains to address real-world problems.

2.10. Hybrid Approach, Searching, and Optimization

A "hybrid approach" combines several methods or systems to create a novel and improved model. Consequently, depending on the needs, a hybrid strategy incorporates the essential principles mentioned above. For example, Sarker et al. [39], developed an efficient context-aware framework for smart mobile services by combining machine learning and knowledge-based expert systems. Instead of employing typical handcrafted static rules, this hybrid context-aware model uses machine learning techniques to find context-aware rules that serve as the knowledge basis of an expert system, making computing and decision-making processes more intelligent and actionable.

2.10.1. Applications

[64] combines fuzzy logic, deep learning, and natural language processing to improve Twitter sentiment analysis accuracy. In [71], the authors offer a deep convolutional neural network-based system for autonomous and robust object recognition in X-ray baggage inspection. Deep learning is combined with computer vision analysis. A fuzzy weighted association rule mining technique was presented by Kang et al. [49] to generate a customer satisfaction product form. Additionally, Sarker et al. covered a range of ML [4] and DL [22] approaches and their hybridization, which may be used to address several real-world issues in a wide range of application domains, including cybersecurity, smart cities, business, finance, and healthcare. Hence, integrating several approaches could be crucial to creating a useful AI model in the field.

Search algorithms tend to be either educated (also known as heuristic search) or uninformed (also known as blind, brute-force) depending on the type of problem. Breadth-first, depth-first, uniform cost search, and other general-purpose search algorithms that produce search trees without depending on domain knowledge are referred to as "uninformed search"[72]. Knowledgeable search [72] in contrast, algorithms—such as greedy search, A* search, graph search, etc.—use extra or problem-specific knowledge during the search process. For instance, to accurately navigate the distance, time covered, and real-time traffic updates on a certain route, one must enter details like their position from the present location when searching on Google Maps. Numerous complex issues that cannot be resolved in any other way can be resolved with informed search. Moreover, evolutionary computation uses optimization search methods like genetic algorithms, which have a lot of promise for resolving practical problems. For example, an algorithm is employed in the cybersecurity field to detect anomalies in the fog computing environment through efficient feature selection [73]. In [74], machine learning techniques are employed to identify Android malware by optimal feature selection utilizing a genetic algorithm. AI-powered search uses data to automatically give accurate and relevant results. Hybridization can incorporate both searching and optimization strategies to create AI models that address real-world challenges.

3. Application of AI in developing Smart Systems

1. A framework was presented to integrate blockchain into AI-assisted manufacturing systems [75]. The special needs of manufacturing blockchains (BCs) were highlighted over generic blockchains. The paper outlined ways in which manufacturing could benefit from the synergy between AI and BC. It discussed how blockchain and AI could accelerate early-phase product design, enhance collaboration, improve processes, secure supply chains, and promote ethical consumerism.
2. The FedLabSync algorithm proposed in [76] advanced Federated Learning (FL) by addressing challenges of data heterogeneity and privacy in decentralized industrial settings. Its ability to integrate diverse machine learning architectures through penalized collaborative optimization and label synchronization enhanced its applicability across real-world scenarios. The inclusion of case studies, such as product inspection in Bosch factories and Remaining Useful Life predictions for aircraft components, demonstrated its potential to deliver results comparable to centralized learning methods while preserving data privacy. However, the scalability of FedLabSync to large networks, its dependency on label synchronization, and implementation complexity in industrial environments required further exploration.
3. The authors [77] investigated the impact of AI, Industry 4.0 readiness, and the Technology Acceptance Model (TAM) on accounting and auditing methods, focusing on their roles in improving processes. Using Big Data, Cloud Computing, and Deep Learning, the research highlighted how these technologies enhanced decision-making, optimized costing, and streamlined audit processes. Convenience and snowball sampling methods yielded 228 respondents from Saudi organizations, uncovering a positive relationship between perceived ease of use, perceived utility, and AI adoption. The findings emphasized the need for user-friendly AI systems to facilitate integration into professional accounting and auditing practices. Additionally, the study underscored the role of AI technologies in automating mundane tasks, reducing human error, and leveraging advanced analytics for improved audit quality and competitiveness.
4. The paper [78] introduces the Convolutional Neural Network–Block Development Mechanism (CNN-BDM), a lightweight deep learning architecture for detecting pallet racking damage in manufacturing and warehousing. With just 6.5 million parameters, it is the first custom CNN for this domain. Using real warehouse data, the model achieved over 90% baseline accuracy, and regularization with a 50% dropout rate boosted performance, achieving 99% precision, recall, and F1 score. The model maintained an F1 score of 96% on test data. This work contributes to Industry 4.0 by applying AI to improve maintenance and safety in industrial settings with an efficient and scalable solution.
5. The authors in [79] introduced a new framework called FSBCIP (Function-Structure-Behavior-Control-Intelligence-Performance) to guide the integration of digital twins in SMS design. The paper reviewed existing definitions, frameworks, design steps, enabling technologies, new blueprint models, and research directions within the field. By providing insights into the integration of digital twins, the

paper addressed industrial needs in the context of Industry 4.0, emphasizing the use of digital technologies to enhance manufacturing processes.

6. The authors [80] proposed a machine vision model that combined the identification of defective products with the continuous improvement of manufacturing processes by predicting the most suitable parameters for production to achieve defect-free items. The suggested model exploited data generated from various integrated technologies in the manufacturing chain, meeting quality management requirements in the context of Industry 4.0. Predictive analysis identified patterns in data and suggested corrective actions to ensure product quality. A comparative study of machine learning algorithms was conducted to evaluate the system. The results indicated that the proposed model largely met requirements for proper implementation.
7. The proposed industrial blockchain-based Product Lifecycle Management (PLM) framework [81] addressed the core challenges of openness, interoperability, and decentralization in Industry 4.0. By integrating blockchain with IoT, M2M, and smart contracts, the framework delivered a secure, efficient, and scalable solution for managing product lifecycle data and services. Despite limitations in real-world validation and stakeholder adoption challenges, the study offered a strong foundation for future research and industrial implementation. The framework held promise for transforming PLM, fostering improved collaboration among stakeholders, and enhancing the efficiency of product lifecycle processes in Industry 4.0.
8. [82] presented a review of literature on Product Defect-Detection Technology in Complex Industrial Processes and its importance to industrial product quality. The paper reviewed and discussed the progress in moving from classic approaches to defects' detection to deep-learning methods. It emphasized the increasing role of advanced defect detection and specific features, including 3D object detection, high accuracy, short detection times, and detection of small or obscured objects. Future trends identified included sensor equipment built into products, online defect detection, and research in 3D technology for defect detection.
9. Luo et al. [83] took up a significant subject on artificial intelligence (AI) in Industry 4.0 through an evaluation of the performance and perception of AI chatbots in conversational commerce. AI, being one of the main enablers of Industry 4.0, enabled businesses to become automated and improved customer interfaces through intelligent means. This research acknowledged that concealed AI chatbots were as efficient as skilled human operators and four times as efficient as newcomers in influencing consumer sales. However, the study revealed a critical challenge: erasing chatbot identity before conversations led to a decrease in the rate of purchases by at least 79.7%. This decrease was attributed to customers' prejudices against disclosed bots being less knowledgeable and less empathetic, even if competent. The study suggested strategies such as late timing of disclosure and informative letters referencing customers' experiences with AI to alleviate the negative impacts. The results of the study held implications for enhancing AI effectiveness at customers' points of contact and initiating bureaucratic changes in human-AI interactions in the context of Industry 4.0.
10. O'Donovan et al. [84] provided a comparison of real-time performance and reliability in implementing conventional cloud computing and fog computing paradigms. The study was designed for Industry 4.0 real-time applications with incorporated ML, and it analyzed latencies and failure frequencies under varying conditions. The authors claimed that although reliability and latency in centralized cloud computing and decentralized computing technology were integrated into the interfaces of CPS to develop real-time intelligent learning solutions for Industry 4.0, communication failure rates could rise to 6.6% under varying stress levels applied to the cloud interfaces.

Table 1. Table for Critical Analysis

References	Year	Objective	Significance	Limitation
[75]	2024	Integration of blockchain into AI-assisted	Enhanced early-phase product	Specific focus on manufacturin

		manufacturing systems	design, secure supply chains	g, generalizability to other sectors not extensively explored
[76]	2024	Federated Learning in industrial settings	Preserved data privacy, comparable performance to centralized methods	Scalability issues in large networks, label synchronization dependency
[77]	2024	Technology Acceptance Model (TAM)	Enhanced decision-making, optimized costing, streamlined audit processes	Need for user-friendly systems, potential bias in convenience sampling
[78]	2023	CNN-BDM for detecting pallet racking damage	High accuracy in damage detection, efficiency in industrial maintenance	Specific to pallet racking damage, applicability to other domains not explored extensively
[79]	2021	FSBCIP framework for digital twins	Enhanced manufacturing processes through digital twin integration	General applicability across diverse industrial contexts
[80]	2021	Machine vision model for defect detection	Predictive quality management, improvement of manufacturing processes	Evaluation limited to machine learning algorithms, scalability in complex manufacturing environments
[81]	2020	Blockchain-based PLM framework	Secure, scalable product lifecycle	Validation challenges,

			management, improved collaboration	stakeholder adoption
[82]	2020	AI based 3D object detection	High-precision, rapid defect identification,	Implementation challenges such as data quality and computational costs
[83]	2019	AI chatbots in conversational commerce	Improved customer interfaces, efficiency in influencing sales	Decreased purchase rates with disclosed AI identity
[84]	2019	Fog computing vs. cloud computing for real-time applications	Improved reliability, reduced latency in Industry 4.0 applications	Increased communication failure rates under stress levels

The performance of artificial intelligence (AI) modeling in creating intelligent and smart systems are also discussed in the paper. It introduces techniques including machine learning, deep learning, fuzzy logic and knowledge representation and their relevance to fields including health, security, smart city intelligence among others. It elaborates the role of AI in automation and intelligent decision making along with hybrid and context aware aspects. While the best results are demonstrated such as AI's flexibility, there is still much to learn about the mechanisms for integrating AI for the best results. The paper admits shortcomings such as real-world problem nature, the demand for large and clean data set for model development. Furthermore, it reveals drawbacks of conventional AI approaches including limitations related to data inputs from specific domains and its bounded capability of machine learning from learning datasets containing imperfect bias.

4. Future Scope

AI has caused a revolution in industries by simplifying general work processes and integrating smart systems into industries. Industry 4.0 as described in the document above refers to a combination of AI with IoT and cyber-physical systems leading to improvement of efficiency and adaptability of industries. However, few factors of the AI solutions and diversity of the data are still a hindrance. The value of AI is in its self-improvement; it is that uncovers innovations such as self-driving automobiles and targeted treatment. There are issues like data privacy, algorithms being coded in one approach, or that machines take over human positions of employment. AI systems demand significant data, and people worry about their monitoring and collection without their consent. Finally, bias training data leads to a prejudiced decision towards the candidates in terms of employment or in matters of law enforcement. Such implications require reflective solutions that include technologies like transparent AI systems and demeanor along with other concepts like ethical AI design and organizational novel workforce programs. The integration of AI with IoT and edge computing is perhaps the biggest shift towards real time analytics and real time decision making. IoT devices continually provide massive amounts of data, and edge computing enables processing this data closer to where it occurs, thereby minimizing latency and the band width needed.

5. Conclusion

Advanced AI modeling is the backbone of solving numerous real-life problems and is implemented across all industries as an innovation catalyst. Although there have been many advancements, issues regarding scalability, ethical concerns, and interpretability still need to be addressed for the next generation of AI innovations. Critical analysis of the current challenges reveals that while AI holds vast potential, significant work remains in overcoming the barriers of data privacy, security, and standardization. Moreover, researchers must continue to innovate and find solutions to these issues to unlock the full potential of AI. The future development of AI promises greater integration into smart system applications, creating new opportunities and advancing the possibilities across various sectors. Despite these advancements, it is essential to acknowledge that unresolved challenges in ethical AI, privacy protection, and interpretability may limit the effectiveness and trustworthiness of AI technologies if not handled carefully. This paper, however, emphasizes the importance of AI-based modeling in realizing automation, intelligence, and the smart systems paradigm in the 4IR era. It has applications in enhancing organizational operations, improving user experiences, and providing innovative solutions to existing challenges, all while recognizing the need for continued critical analysis to ensure these technologies evolve in a responsible and sustainable manner.

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