Review of Artificial Intelligence and Machine Learning Technologies Classification

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Abstract— Artificial intelligence (AI) represents a dynamic set of technologies designed to address various practical problems. At its core, AI relies on machine learning (ML), which employs intricate algorithms to tackle classification, clustering, and forecasting challenges. The potential applications of AI and ML are quite promising, prompting intensive research in this field. However, widespread industrial and societal utilization of AI remains limited. The obstacles to broader AI adoption must be examined from both internal AI-related issues and external societal factors. Addressing these challenges is essential to realizing the full potential of AI technologies in industry and society. This paper identifies and discusses the hurdles to implementing AI technologies in economies and societies heavily reliant on resources. The categorization of AI and ML technologies is based on existing publications, enabling us to pinpoint organizational, personnel, social, and technological constraints. The paper also outlines research directions in AI and ML aimed at mitigating these limitations and expanding the applications of AI and ML.

Key words: Artificial Intelligence; Machine Learning; Deep Learning; Explainable Machine Learning; AI Challenges

I. INTRODUCTION

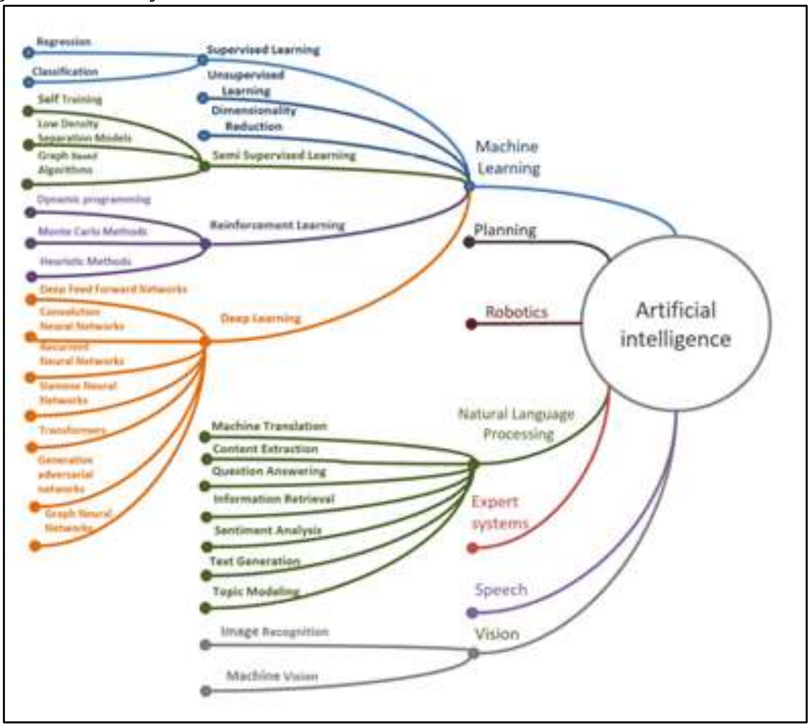
Artificial intelligence (AI) is the ability of a machine to perform tasks that would normally require human intelligence. AI can be used to solve a wide range of problems, including speech recognition, image recognition, and natural language processing. Machine learning (ML) is a type of AI that allows machines to learn from data without being explicitly programmed. ML is used in many different applications, including spam filtering, product recommendations, and medical diagnosis. Natural language processing (NLP) is a field of computer science that deals with the interaction between computers and human language. NLP is used in many different applications, including machine translation, text summarization, and question answering. The following are some examples of how AI, ML, and NLP are used in different industries:

1) Healthcare: AI can be used to develop new drugs and treatments, diagnose diseases, and provide personalized care. Finance: AI can be used to detect fraud, manage risk, and provide investment advice. Manufacturing: AI can be used to automate tasks, optimize production, and improve quality control. Retail: AI can be used to personalize recommendations, optimize inventory, and combat fraud. Transportation: AI can be used to develop self-driving cars, optimize traffic flow, and predict demand.AI, ML, and NLP are rapidly transforming many industries, and they have the potential to revolutionize the way we live and work. Some specific examples of how AI, ML, and NLP are used in the scientific and applied domains are as follows:
2) Chemistry: AI and ML can be used to predict the properties of molecules and to design new materials.
3) Medicine: AI and ML can be used to diagnose diseases, develop new drugs and treatments, and personalize care.
4) Astronomy: AI and ML can be used to analyze astronomical data and to discover new planets and galaxies.
5) Computational biology: AI and ML can be used to study the structure and function of proteins and nucleic acids, and to develop new drugs and treatments.
6) Agriculture: AI and ML can be used to optimize crop yields, to detect pests and diseases, and to predict market prices.
7) Municipal economy: AI and ML can be used to manage traffic, to optimize energy consumption, and to provide public services.
8) Industry: AI and ML can be used to automate tasks, to optimize production, and to improve quality control.
9) Construction: AI and ML can be used to design buildings, to plan construction projects, and to manage construction costs.
10) Environmental modeling: AI and ML can be used to model climate change, to predict natural disasters, and to assess the environmental impact of human activities.
11) Geo-ecological processes: AI and ML can be used to study the structure and function of the Earth's crust, to predict earthquakes and other geological hazards, and to manage natural resources.
12) Petrographic studies: AI and ML can be used to identify and classify minerals, to analyze rock formations, and to assess the quality of petroleum reserves.
13) Mineral exploration: AI and ML can be used to identify potential mineral deposits, to plan exploration activities, and to assess the economic viability of mineral exploration projects.
14) Mining forecasting: AI and ML can be used to predict the production of minerals, to forecast the demand for minerals, and to assess the impact of mining activities on the environment.
15) Natural language processing: AI and ML are used in many different NLP applications, including machine translation, text summarization, and question answering.

These are just a few examples of the many ways that AI, ML, and NLP are being used in the scientific and applied domains. As these technologies continue to develop, we can expect to see even more innovative and groundbreaking applications emerge.

II. HIERARCHY OF ARTIFICIAL INTELLIGENCE

Classical artificial intelligence hierarchy is as follow.



Artificial intelligence, often referred to as AI, involves the capacity of a digital computer or computer-controlled robot to carry out tasks typically associated with intelligent beings. The system's level of intelligence is assessed concerning its similarity to human intelligence. In contemporary applications, weak or soft AI is predominantly used, which excels at addressing specific problems, demonstrating practical accuracy. Research in this field can also encompass strong or general artificial intelligence. AI encompasses several key scientific domains, including machine learning, natural language processing (NLP), text and speech synthesis, computer vision, robotics, planning, and expert systems. These domains are visually represented in Figure 3, as created by the authors based on their research materials.

Machine learning and deep learning[4] together is a type of artificial intelligence that allows machines to learn from data without being explicitly programmed. It is used in a wide range of applications, including speech recognition, image recognition, natural language processing, economic planning, manufacturing control, expert systems, and robotics. Machine learning is also used to solve scientific and applied problems in a variety of fields, such as chemistry, medicine, astronomy, computational biology, agriculture, municipal economy, industry, construction, environmental modelling, geo-ecological processes, petrographic studies, mineral exploration, and mining forecasting. In short, machine learning is a powerful tool that is being used to revolutionize many different industries and fields of study.

ML methods are divided into several classes depending on the learning method and purpose of the algorithm [6] and include the following: supervised learning (SL) [2], unsupervised learning (UL) or cluster analysis [3], dimensionality reduction, semi-supervised learning (SSL), reinforcement learning (RL) [7], and deep learning (DL) [8]. UL methods solve the task of splitting the set of unlabelled objects into isolated or intersecting groups by applying the automatic procedure based on the properties of these objects [9,10]. UL reveals the hidden patterns in data, as well as anomalies and imbalances. SL methods solve classification or regression issues. Such problems arise when a finite group of specifically marked objects is allocated in a potentially infinite set of objects. If the objects are marked by a finite set of integers (class numbers), then the classification problem is implemented. The classification algorithm, using this group as an example, must mark the objects, which have not yet been designated, with one of the indicated numbers. If the objects are marked with real numbers, both integer and fractional, then the problem of regression recovery is implemented. The algorithm selects a real number for unlabelled objects based on previously marked objects. In this case, the problems of prediction or filling the gaps in the data are solved. DL methods solve the problem of revealing the hidden properties in data arrays by using neural networks with a large number of hidden layers and networks of a special architecture.

In the context of DL, the concept of transfer learning (TF) is frequently mentioned. TF means improving "a learner from one domain by transferring information from a related domain" [11]. Without claiming to be comprehensive, the classic SL models comprise the following types: k-nearest-neighbour (k-NN) [12,13], logistic regression [14], decision tree (DT), support vector machines (SVM) and feed forward artificial neural networks (ANN) . The classic UL models include the following types: k-means and principal component analysis (PCA).

The contemporary UL models are as follows: isometric mapping (ISOMAP) , locally linear embedding (LLE) [75, t-distributed stochastic neighbor embedding (t-SNE) , kernel principal component analysis (KPCA) , and multidimensional scaling (MDS). The contemporary SL, SSL, RL, DL models include the ensemble methods (boosting , random forest, etc.) and deep learning long short-term memory (LSTM) [15], deep feed forward neural networks (DFFNN) , convolutional neural networks (CNN) , recurrent neural networks (RNN) , etc. Deep learning is the fastest growing AI sub-domain. DL is a set of methods that employs the so-called deep neural networks, in other words, the networks containing two or more hidden layers. The main advantage of the deep architectures is related to the ability to solve the tasks using the end-to-end method. This approach reduces the requirements towards preliminary data processing, since a signal or image vector is used as an input to the network, and the network independently identifies the regularities relating the input vector to the target variable. The network performs the labour-intensive and complex process of selecting the significant features. This network functioning greatly simplifies the task of the researcher. However, these advantages appear only with a sufficiently large amount of training data and correctly chosen neural network architecture. There are three basic architecture types among the dozens of architectures.

1) Standard feed-forward neural network (FFNN).
2) Recurrent neural network (RNN).
3) Convolutional neural network (CNN).
4) Hybrid architectures, including elements of 1, 2, 3 basic architectures, for example, Siamese networks and transformers.

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