A Review of Artificial Intelligence and Machine Learning Technologies: Classification, Restrictions, Opportunities and Challenges

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ABSTRACT: Artificial intelligence (AI) is an evolving set of technologies used for solving a wide range of applied issues. The core of AI is machine learning (ML)—a complex of algorithms and methods that address the problems of classification, clustering, and forecasting. The practical application of AI&ML holds promising prospects. Therefore, the researches in this area are intensive. However, the industrial applications of AI and its more intensive use in society are not widespread at the present time. The challenges of widespread AI applicationsneed to be considered from both the AI (internal problems) and the societal (external problems) perspective. This consideration will identify the priority steps for more intensive practical application of AI technologies, their introduction, and involvement in industry and society.

Keywords: Artificial Intelligence; Machine Learning; Deep Learning; Explainable Machine Learning; AIChallenges

1. INTRODUCTION

Artificial Intelligence (AI) research is thriving within the scientific community, with a significant focus on theoretical exploration and practical applications across various societal domains. Machine Learning (ML) methods, a cornerstone of AI, enable the extrapolation of new data properties from known training data. Deep Learning (DL), a subset of ML, has garnered substantial attention in recent years, evidenced by the growing volume of publications within scientific databases. Figure 1 displays the escalating trend of reviewsin AI, ML, and DL on Scopus from 2000 to 2021, indicative of the escalating interest and research activity in these fields.

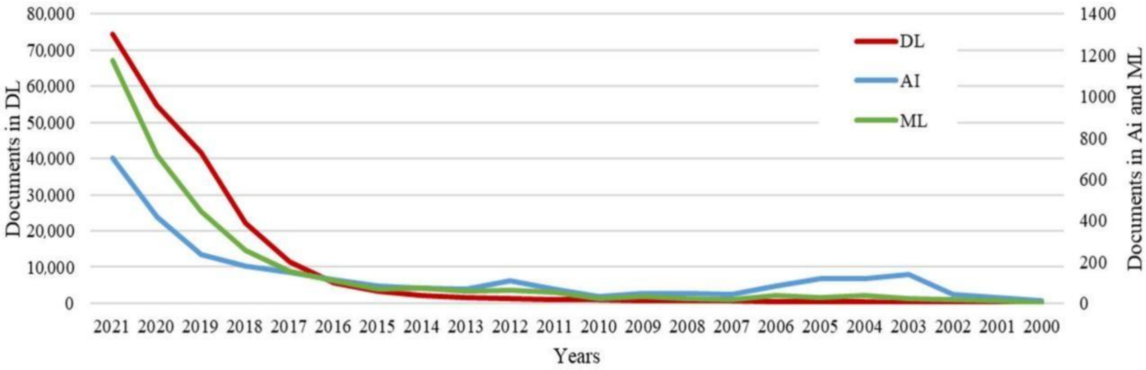
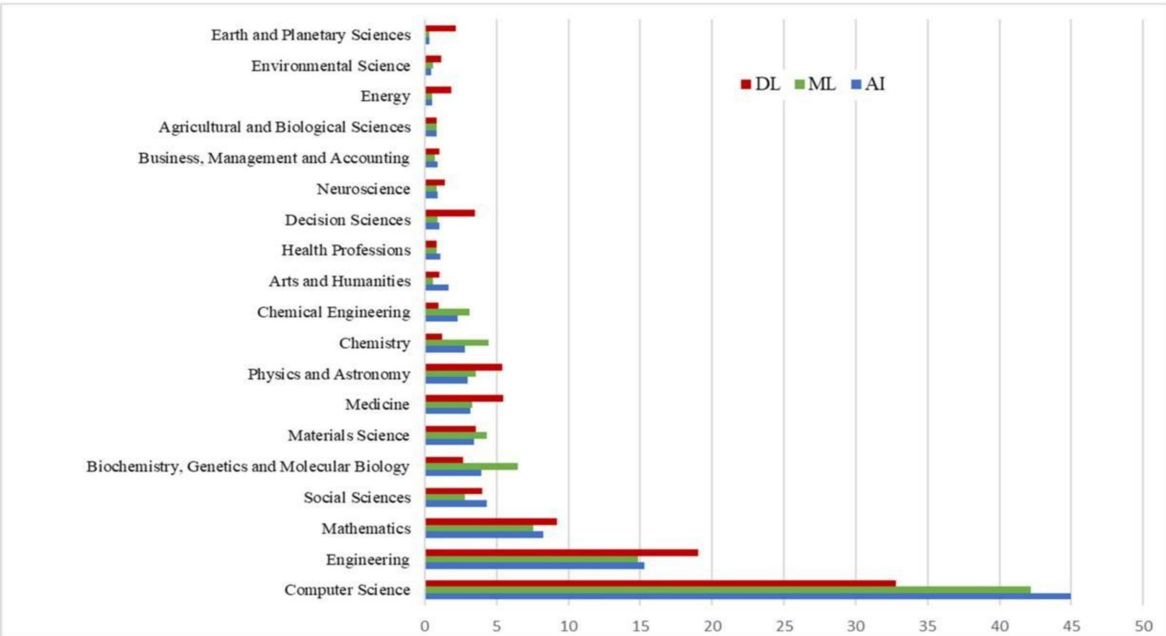


Figure 1. The number of review studies devoted to artificial intelligence (AI), machine learning (ML), and deep learning (DL) indexed in Scopus.

Methods of AI have many practical applications. The applications, which are most often discussed in scientific publications, are shown in **Figure 2**. The dominant areas of AI, ML, and DL studies are computer science, engineering and mathematics .

Figure 2. Ranking of the reviews in Scopus according to the areas of application



(percentage). Source: generated by the authors.

<u>2.</u> Artificial Intelligence and Machine Learning Technologies Classification:-

:Artificial intelligence (AI) refers to the capacity of a digital computer or computer-controlled robot to execute tasks typically associated with intelligent beings [30]. It encompasses software and hardwaremethods that emulate or replicate human behavior and cognition. AI is categorized into weak AI and strong AI, or general artificial intelligence

[31], depending on the system's "intelligence level" relative to humans [32,33]. Contemporary practical applications predominantly utilize weak or soft AI, capable of solving specific problems with satisfactory accuracy. Strong or general artificial intelligence is the focus of research [31]. AI spans various scientific domains including machine learning, natural language processing (NLP), text and speech synthesis, computer vision, robotics, planning, and expert systems, as depicted in Figure 3, compiled by the authors based on various sources [7,34,35].

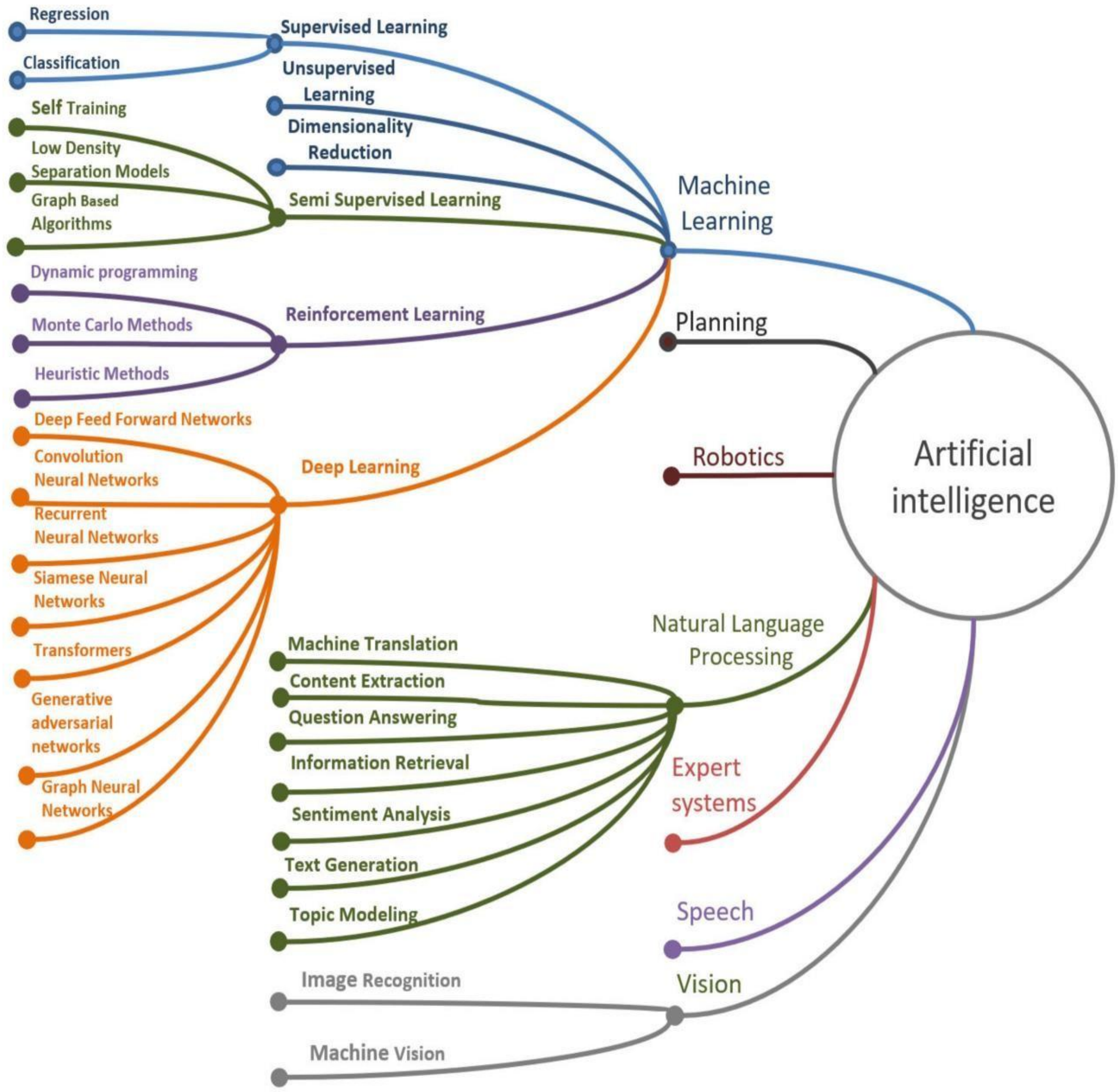
A large number of the AI applications are built on the basis of machine learning methods; these methods implement the fundamental idea of AI [36]. ML is applied to achieve better results in speech recognition [37] and speech emotions [38]. A wide range of ML methods are used in economic planning
[39] and manufacturing control [40]. Ref. [41] notes that ML is a powerful tool for data analysis, and it can be used in various expert systems [42]. Machine learning is currently one of the main areas of the researchesin the field of robotics [10,43].

Machine learning is often used to solve scientific and applied problems. For example, the ML applicability conditions [44] and the promise of deep learning [45] are considered for solving problems in the field of chemistry. There are numerous cases of applying ML in medicine [46,47], especially for medical imaging [5], astronomy [48], computational biology [49,50], agriculture [51], municipal economy [52] and industry [53], construction [54], modeling environmental [55] and geo-ecological processes [56], petrographic studies [12,57] exploration [58] and forecasting of mining [59], etc. ML is actively used and in fact, it is the core of modern investigations in the field of natural language processing [8,60,61].

ML methods are divided into several classes depending on the learning method and purpose of the algorithm [62] and include the following: supervised learning (SL) [13], unsupervised learning (UL) or cluster analysis [14], dimensionality reduction, semi-supervised learning (SSL), reinforcement learning (RL)[63], and deep learning (DL) [64].

UL methods solve the task of splitting the set of unlabeled objects into isolated or intersecting groups by applying the automatic procedure based on the properties of these objects [65,66]. 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



Machine learning (ML) methods are categorized into various classes based on their learning approach and intended use. These include:

1. Supervised Learning (SL)
2. Unsupervised Learning (UL) or Cluster Analysis
3. Dimensionality Reduction
4. Semi-supervised Learning (SSL)
5. Reinforcement Learning (RL)
6. Deep Learning (DL)

Unsupervised Learning (UL) methods aim to partition a set of unlabeled objects into distinct or overlapping groups using automated procedures based on object properties. UL uncovers hidden patterns, anomalies, andimbalances within the data.

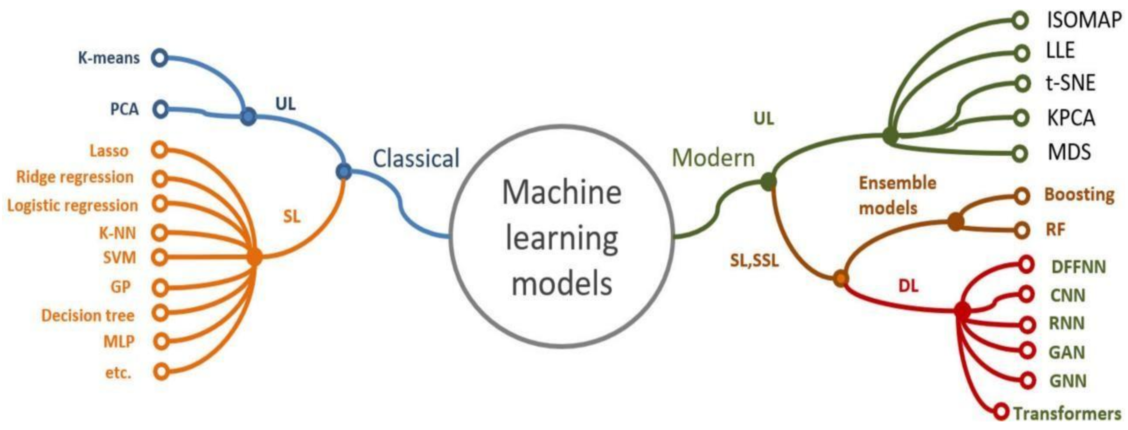
On the other hand, Supervised Learning (SL) methods address classification or regression tasks. In classification, a finite group of specifically labeled objects is allocated within a potentially infinite set. If the labels consist of a finite set of integers (class numbers), it's a classification problem. The algorithm must assign unlabeled objects one of the indicated numbers. In regression, where objects are labeled with real numbers, both integer and fractional, the algorithm predicts a real number for unlabeled objects based on previously labeled ones, effectively addressing prediction or data gap filling tasks.

Deep Learning (DL) methods tackle the task of uncovering hidden properties within data arrays by utilizing neural networks with numerous hidden layers and specialized network architectures.

In the realm of Deep Learning (DL), the concept of transfer learning (TF) is frequently discussed, referring to the enhancement of a learner from one domain by leveraging information from a related domain. MachineLearning (ML) models can be categorized into classical and modern types (refer to Figure 4) . While not exhaustive, classic Supervised Learning (SL) models encompass:

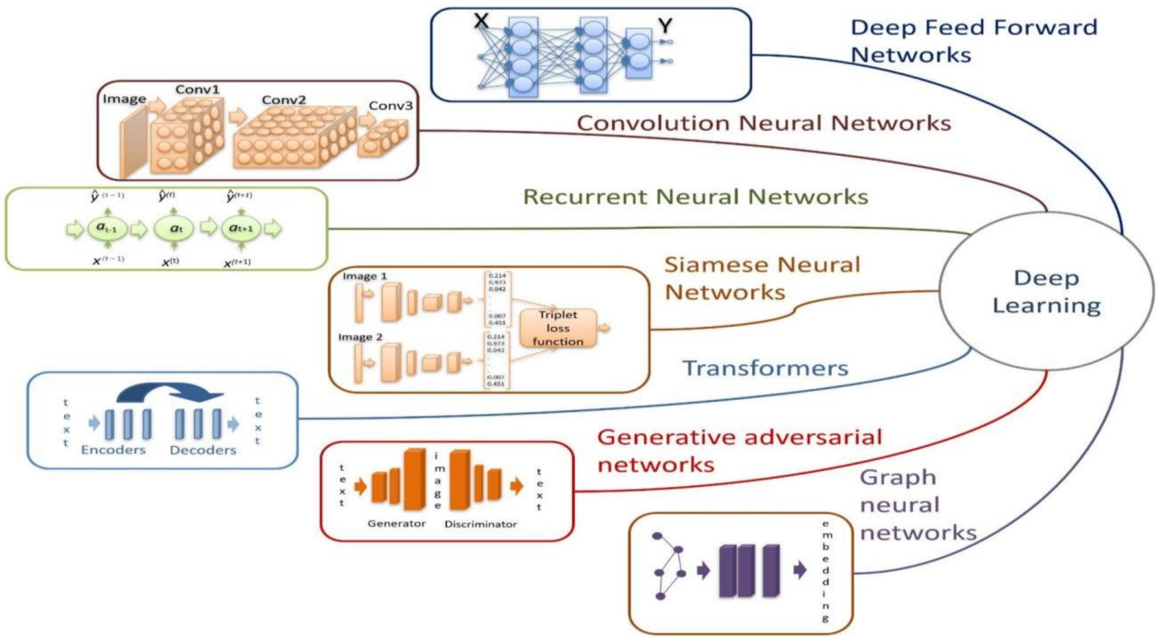
1. k-nearest-neighbor (k-NN)
2. Logistic Regression
3. Decision Tree (DT)
4. Support Vector Machines (SVM)
5. Feed Forward Artificial Neural Networks (ANN)

Similarly, classic Unsupervised Learning (UL) models consist of:
1. k-means
2. Principal Component Analysis (PCA).



Among the plethora of architectures, there exist three fundamental types [83], from which various modifiedmodels are derived :

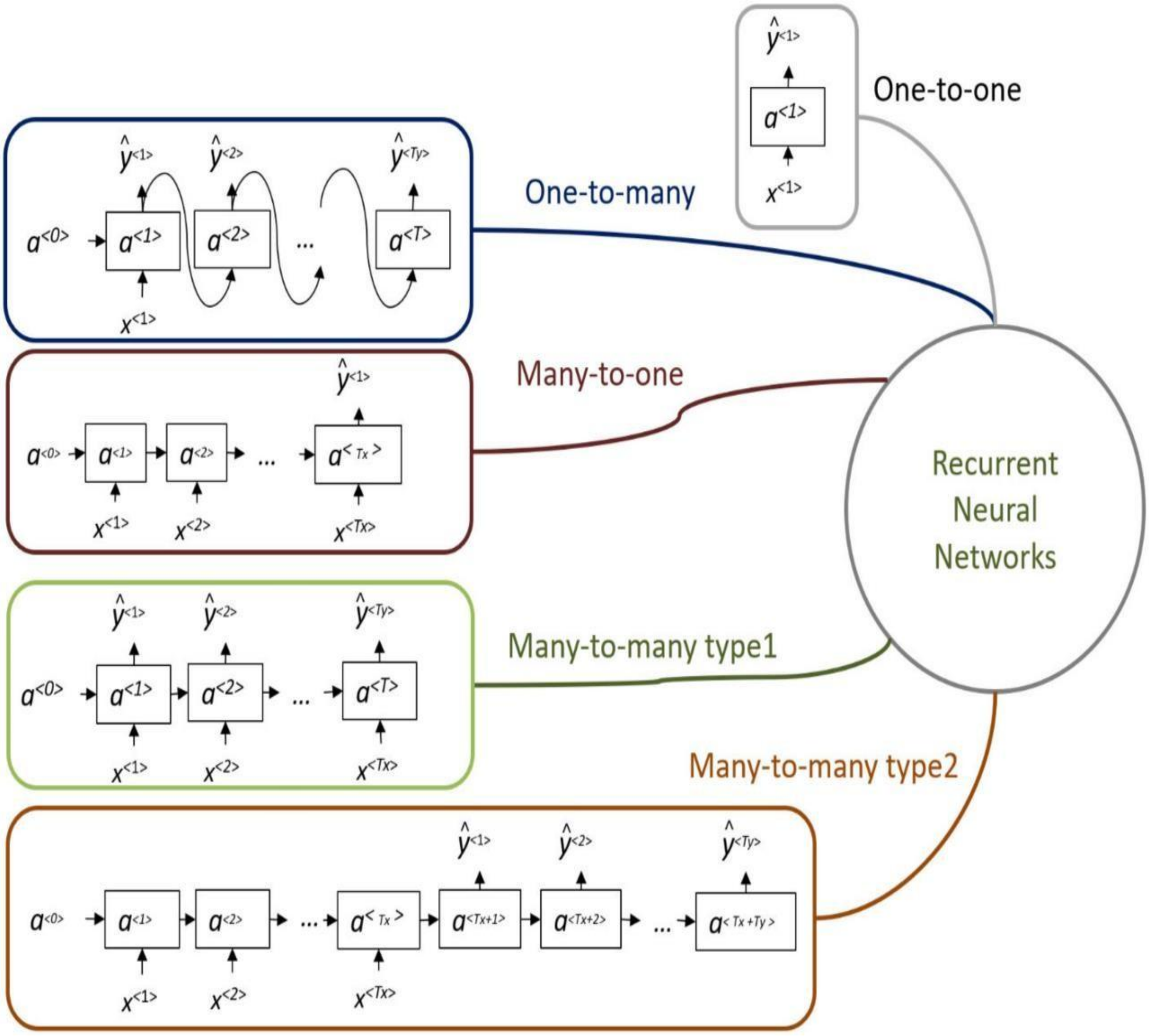
1. Standard Feed-Forward Neural Network (FFNN).
2. Recurrent Neural Network (RNN).
3. Convolutional Neural Network (CNN).



Feed forward neural networks (FFNN) are widely used in practice to solve classification problems and the regression.

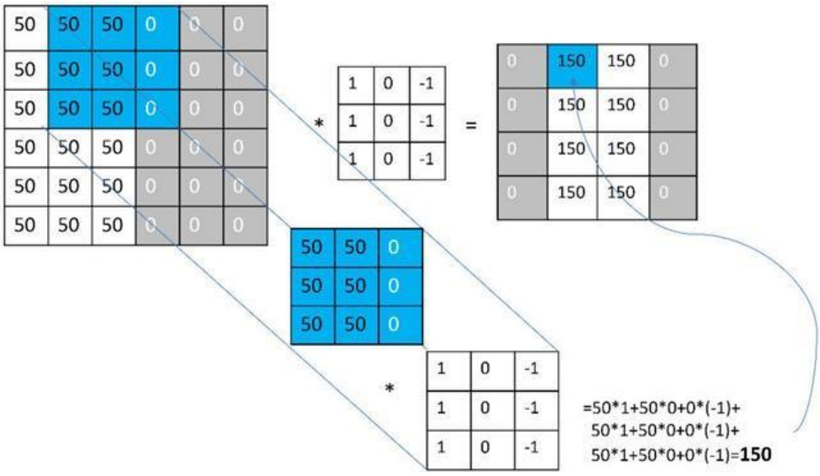
Recurrent neural networks (RNN) can use signal sequences as input data, including those of different lengths. vThe one-to-many architecture is employed to address scenarios where a relatively concise sequence of input data leads to the generation of extended sequences of data or signals. This is exemplifiedin tasks such as music generation or text generation , where merely setting the style of a musical piece or the theme of a narrative is adequate.

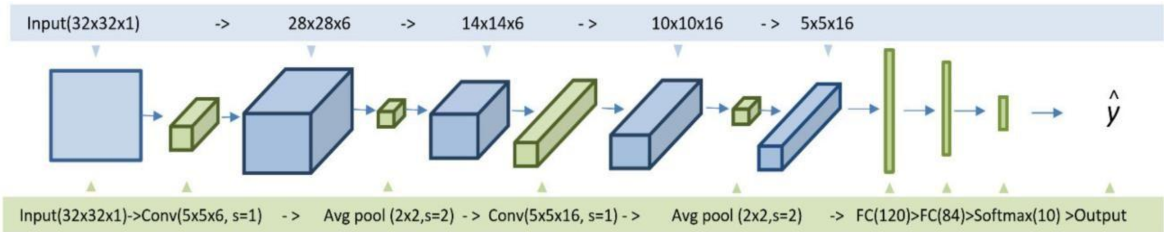
On the other hand, the many-to-one architecture finds application primarily in classification tasks. For instance, in sentiment analysis, where the emotional tone of a text is assessed, the text's tone—expressed through class assessments like neutral, negative, or positive—is determined not only by individual words butalso by their combinations. Another task suited for the many-to-one architecture is named entity recognition, which involves identifying entities such as proper names, days of the week, months, locations, dates, and so forth. Additionally, determining gene values in DNA analysis is accomplished by analyzing nucleotide sequences.



Convolutional neural networks (CNNs)

Make it possible to single out the complex regularities in the presented data; these regularities are invariant with respect to their location in the input signal vector. They are exemplified by horizontal or vertical lines, or other characteristic features in the image. The formation of convolutional filters, or to be more precise, the adjustment of the weights of the neurons modeling such a filter, occurs in the process of network training. Due to the implementation of the convolution operation, the computational complexity of the training process remains within the reasonable limits. CNNs have shown exceptional results in image processing tasks.





3. Limitation and Difficulties in the AI and ML Application:-

There are promising prospects for the widespread use of AI. In general, the economic prospects of AI application are highly rated. According to [24], the economic effect in the European health care system is about 200 billion euros. This effect is associated with saving time and increasing the number of saved lives. Refs. [16,17] perform the results of AI imple- mentation in various economic sectors. According to estimates [17,25], a significant effect from the use of AI is observed in commerce (USD 400 billion), logistics (USD 400 billion), automated production (USD 300 billion), banking (USD 200 billion). In percentage terms, the greatest effect (up to 10% of profit growth) is observed in high-tech products. Conse- quently, the economic impact is higher in developed countries, producing more high-tech products compared to the resource-based economies. About a quarter of GDP in Kaza- khstan is formed by the extraction, processing and transportation of resources [18]. Primary products account for 70–75% of exports. The share of innovative products in GDP is 1.6% and only 1% of companies are high-tech [19].

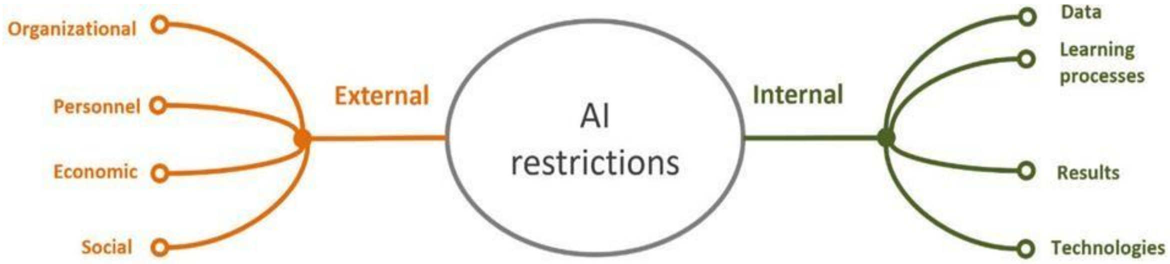
Accordingly, the predicted increase in GDP is associated with the use of AI technologies and can beestimated at 1.5–2%.

Nevertheless, there are a number of obstacles, and overcoming these barriers means new possibilities for AI implementation in manufacturing, and also a new round of techno- logical development of AI.

The scientific community identifies the following types of restrictions: organiza- tional [139], personnel, comprising the fear of new technologies (fear of AI) and shortage of data scientists [140]), problems with data including data quality and the large volume of data [141], legal, economic, social issues, etc. [142]. In particular, the authors of [142] identify the following nine problems: data quality, privacy, and security; data biases and technical limitations; ―black box‖, transparency, and predictability; wealth gap and in- equality; economy of developing countries; job displacement and replacement; trust and adoption; ethical and morality issues; legal issues and regulation policy. The study [32] describes the following ten constraints in the process of solving the medical problems:

1. Insufficient amount of posted data.
2. Sample variability, such as variability in tissue and organ samples.
3. Prevalence of non-binary classification problems.
4. Large image sizes (50,000 × 50,000), while existing deep learning models operate with substantiallysmaller images (608 × 608 Yolo), 224 × 224 VGG16 [143].
5. Turing test dilemma. The final assessment is carried out by a human, which is not alwayspossible.
6. Orientation of weak AI to the solution of one task, which increases the complexity of training andleads to the associativity problem indicated below.
7. High computational costs mean high costs of AI-based solutions.
8. Instability of solutions of the computer vision systems and their dependence on noise in problems ofmedical diagnostics.
9. Lack of transparency and interpretability.

10. Difficulties in applying AI in practice. For example, the difficulties of the Watson Health project [144] are associated with the complexity of the practical application, low confidence inthe results and high costs.

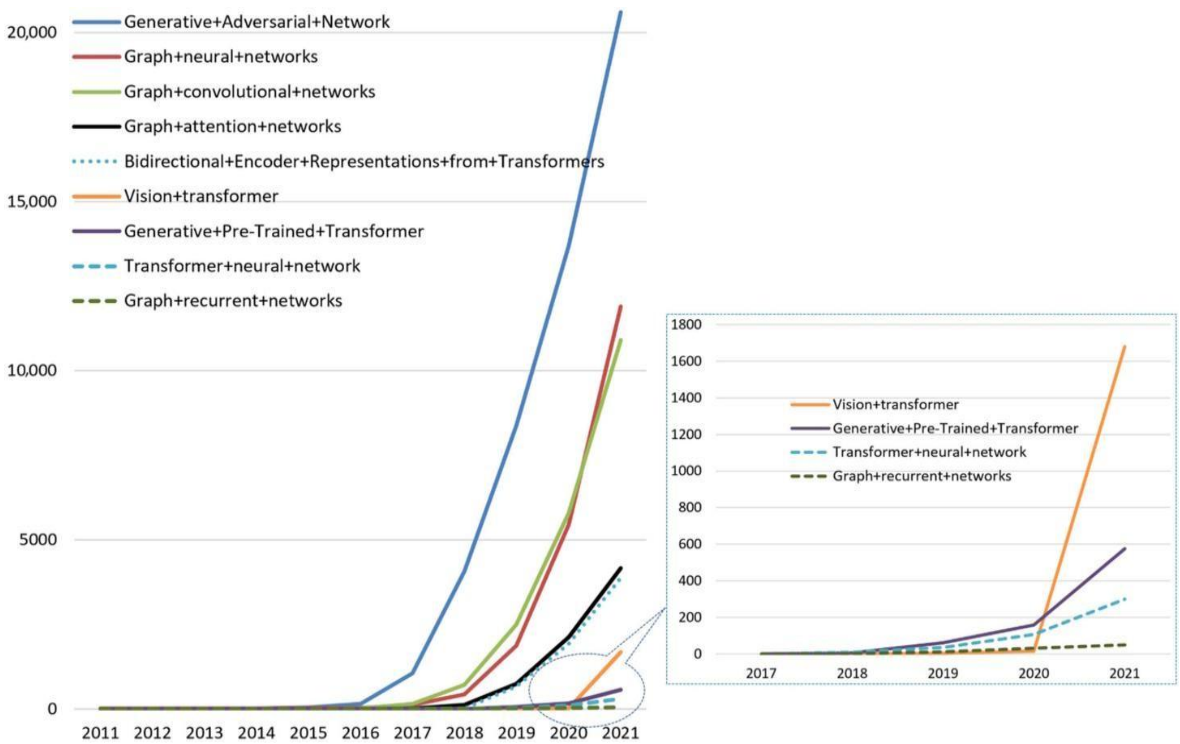


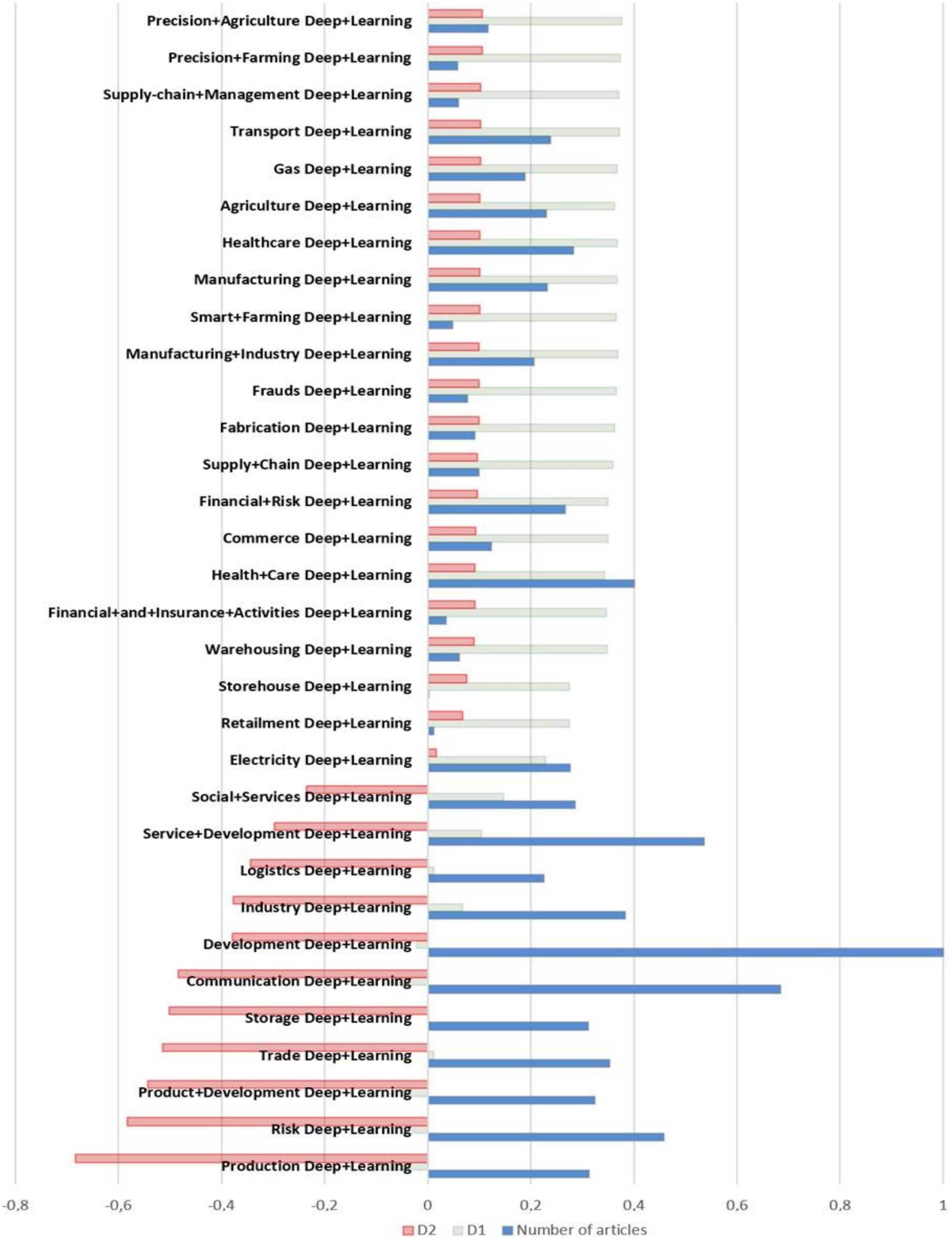
4. DISCUSSION

Despite the significant expectations associated with the use of AI, in many cases, the current level oftechnology is a significant obstacle to their implementation in the manufacturing and service sectors. One must consider the approaches to solving some internal problems of employing the AI technologies and the evaluation of the prospects for overcoming these limitations.

Data generation for training deep ML models. The solution of many problems in the field of deep learning depends on the volume and quality of the data sets (data set—DS). The labeled image packs, such as ImageNet [161], Open Images [162], COCO Dataset [163] and FaceNet, are widely used to solve computer vision problems. However, the existing widely used DS may not be sufficient for solving specific problems, for example, they provide the recognition of a limited number of objects. Therefore, the problem of data shortage in the field of computer vision can be solved via using the synthetic DS created on 3D graphic editors [164], game engines and environments [165–168]. These DS, in particular, are used for training unmanned vehicles [169]. Synthetic datasets are also applied in other areas [57]. Generative adversarial networks have been recently used to generate them [170]. A large-scale review of the approaches to creating the synthetic datasets is presented in [171].

Speed up learning. In cases when the subject area and the problem are close to the available solutions, the acceleration of learning is possible if preliminary trained models are used, according to the transfer learning scheme [67,172]. This means that a neural network previously trained on a large data set can be supplemented with one or more layers. Additional layers are adjusted at the final training phase on a specialized data set, which is usually not large. In this case, all other layers are considered as ―frozen‖, and their weights do not change. It is believed that the preliminary trained network retains the basic patterns that are inherent in a data set of a certain type (faces, landscape, speech, etc.), and additional layers focus on the features of a specialized data set. The use of transfer learning not only speeds up the learning process, but also reduces the requirements of the hardware. **Explaining the results of machine learning models**. Artificial intelligence (AI) has recently achieved great success, dueto the rapid development of the machine learning technologies. Despite this, there are potential risks associated with a ―black box‖ approach to learning. Unlike some classic machine learning methods, especially decision trees, where the results of a model can be explained relatively simply, non-linear classification and especially deep learning models lack transparency, making it difficult to understand how the model made a particular decision. This is a serious problem that hinders the widespread use of AI in healthcare [173], banking and many other areas [174].





5. CONCLUSION:

In conclusion, deep learning stands as the fastest growing domain within AI research, with frequent advancements and versatile applications spanning text, speech, handwriting recognition, image transformation, and temporal sequence processing. Despite this progress, obstacles persist in both technological and socio-economic realms, hindering widespread adoption. Efforts to address these challenges involve overcoming data scarcity, enhancing AI models, and accelerating learning. While strides have been made, significant hurdles remain, particularly concerning resource-based economies. Futureendeavors should focus on bridging technological gaps, expanding accessible datasets, and tailoring methods to specific industry needs like agriculture, healthcare, and finance, emphasizing the potential synergies between remote sensing and machine learning for enhancing productivity and societal outcomes.

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