LITERATURE REVIEW ON THE VARIETY KINDS OF AI AND ML TECHNOLOGIES CLASSIFICATIONS AND LIMITATIONS

Safa Hussein Oleiwi1,
Zahraa Sameer Jawad2,
Yasser Taha Alzubaidi3
1College of Education for Humanities Kerbala University, in Kerbala, Iraq.
2Al-Safwa University College, Department of Computer Engineering Techniques, in Kerbala, Iraq.
3Al-Safwa University College, Department of Medical Instrumentation Techniques Engineering, in kerbala, Iraq.

ABSTRACT:
Artificial intelligence (AI) is a collection of advanced technologies that are employed to tackle various practical problems in a dynamic and progressive manner. Machine learning (ML) is a fundamental component of artificial intelligence (AI) that encompasses a range of algorithms and techniques designed to perform various tasks such as classification, segmentation, and forecasting. The utilisation of Artificial Intelligence (AI) and Machine Learning (ML) in practical settings exhibits significant potential, thereby prompting a multitude of scholarly inquiries in this domain. Nevertheless, the implementation of artificial intelligence in industrial contexts and its ubiquity in the community are presently constrained. In order to comprehend the obstacles linked to the extensive integration of AI, a thorough assessment is imperative, encompassing both intrinsic AI-related concerns and extrinsic societal dilemmas. The objective of this study is to ascertain pivotal metrics that can augment the pragmatic execution of artificial intelligence (AI) technologies, their assimilation across various sectors, and involvement of the community. This article scrutinises and evaluates the challenges that ensue from the integration of artificial intelligence (AI) technologies in the economies and societies of nations that possess abundant resources. The process of standardising the deployment of artificial intelligence (AI) and machine learning (ML) technologies is grounded in the extant literature pertaining to these domains. The utilisation of a systematic approach facilitates the assimilation of diverse constraints, encompassing organisational configuration, human capital, societal influences, and technological facets. The current investigation delves into prospective avenues of research within the fields of Artificial Intelligence (AI) and Machine Learning (ML) that possess the capability to surmount particular constraints and broaden the range of AI and ML implementations.

Keywords: AI, ML, DL, AI and ML of Classification, AI and ML of Limitations.

Introduction

Artificial Intelligence (AI) and Machine Learning (ML) are rapidly evolving fields that have revolutionized various industries. In this literature review, we will explore the varieties of types of AI and ML based on their classification, limitations, potential, and problems [1].

1. Classification of AI and ML: Researchers have categorized AI and ML into various types based on their functionality and approach. Some common classifications include [2]:

a. Supervised Learning: This type of ML involves training a model using labeled data to predict or classify new, unseen data. It is widely used in tasks such as image recognition, sentiment analysis, and spam filtering.

b. Unsupervised Learning: Unlike supervised learning, unsupervised learning algorithms work with unlabeled data to discover patterns or relationships. Clustering and dimensionality reduction are common techniques used in unsupervised learning.

c. Reinforcement Learning: This type of AI involves an agent learning to interact with an environment through trial and error. The agent receives feedback in the form of rewards or penalties, guiding its decision-making process. Reinforcement learning has been successful in game-playing scenarios and robotics.

d. Deep Learning: Deep learning is a subset of ML that utilizes neural networks with multiple layers to process and learn from complex patterns in data. It has achieved breakthroughs in tasks such as image recognition, natural language processing, and speech synthesis.

e. Transfer Learning: Transfer learning leverages pre-trained models and their learned representations to solve new tasks or domains with limited labeled data. It enables faster training and better performance in scenarios with resource constraints.

2. Limitations of AI and ML: While AI and ML have made significant advancements, they still have limitations that researchers are actively addressing [3]:

a. Data Limitations: ML models heavily rely on high-quality and diverse data for training. Limited or biased data can lead to poor generalization and inaccurate predictions. Obtaining labeled data can be time-consuming and expensive.

b. Lack of Explainability: Some AI and ML models, such as deep neural networks, are considered "black boxes" because they lack interpretability. Understanding how and why a model makes certain predictions is crucial in domains such as healthcare and finance.

c. Ethical Considerations: AI and ML systems raise ethical concerns regarding privacy, bias, and accountability. Biased training data can perpetuate discrimination, and automated decision-making systems may lack transparency and accountability.

3. Potential of AI and ML: AI and ML hold tremendous potential across various domains [4]:

a. Healthcare: ML can aid in early disease detection, medical imaging analysis, personalized treatment recommendations, and drug discovery. It has the potential to improve patient outcomes and reduce healthcare costs.

b. Finance: AI and ML algorithms are used for fraud detection, credit scoring, algorithmic trading, and risk assessment. They can automate repetitive tasks and provide more accurate predictions, enhancing decision-making processes.

c. Autonomous Systems: AI and ML are driving advancements in autonomous vehicles, robotics, and smart home devices. These technologies have the potential to enhance safety, efficiency, and convenience in everyday life.

4. Problems with AI and ML: AI and ML also face challenges that researchers are actively addressing [5]:

a. Safety and Security: As AI systems become more autonomous and interconnected, ensuring their safety and protecting against malicious use becomes critical. Vulnerabilities in ML models can be exploited to manipulate their behavior.

b. Job Displacement: The automation potential of AI and ML raises concerns about job displacement. While it can lead to the creation of new roles, it requires reskilling and upskilling the workforce to adapt to changing job requirements.

c. Human-Machine Interaction: Designing intuitive and effective interfaces for humans to interact with AI systems is a significant challenge. Ensuring seamless collaboration and clear communication between humans and machines is crucial for their successful integration.

AI and ML encompass various types, each with its classification, limitations, potential, and problems. While the field has witnessed remarkable progress, challenges remain in terms of data limitations, explainability, and ethical considerations. However, the potential of AI and ML across domains such as healthcare, finance, and autonomous systems is vast, promising significant advancements and benefits to society. Addressing the problems associated with AI and ML, such as safety, job displacement, and human-machine interaction, will be crucial for harnessing their full potential. The visual representation presented in Figure 1 illustrates the apps that are commonly discussed in scientific journals. The principal academic disciplines that underpin the study of artificial intelligence, machine learning, and deep learning are computer science, engineering, as well as mathematics. [6-8].

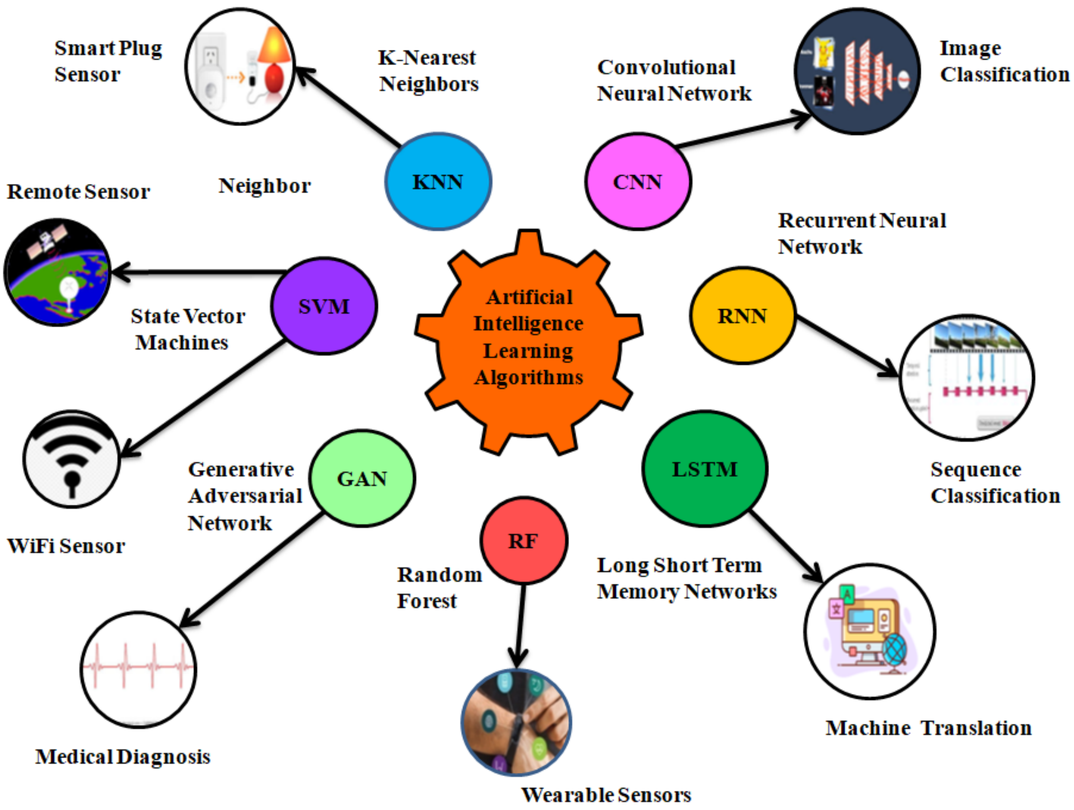

FIGURE 1. - Various applications based on ML and DL-based AI Sensing.[2]

1. RELATED WORK: VARIETIES OF TYPES OF AI BASED ON ML AND DL.

The field of Artificial Intelligence (AI) has witnessed significant advancements in recent years, particularly in the domains of Machine Learning (ML) and Deep Learning (DL). In this section, we will review some key related work that explores the varieties of AI based on ML and DL. Supervised learning has been extensively studied and applied in various domains. [9] introduced convolutional neural networks (CNNs) for image classification tasks, which revolutionized computer vision. Similarly, recurrent neural networks (RNNs) introduced by [10] have been successful in sequence prediction tasks such as natural language processing. Unsupervised learning techniques have been widely explored for learning patterns and structures in unlabeled data. At [11] introduced generative adversarial networks (GANs), which have gained significant attention in the field. GANs can generate realistic synthetic data by training a generator network to deceive a discriminator network. This work has led to applications such as image synthesis, text generation, and data augmentation. Reinforcement Learning (RL) has seen remarkable progress, particularly with the combination of deep learning techniques. At [12] introduced the Deep Q-Network (DQN), which achieved superhuman performance in playing Atari 2600 games solely from raw pixels. Subsequently, researchers have explored more advanced algorithms, such as Proximal Policy Optimization (PPO) and Deep Deterministic Policy Gradient (DDPG), enabling RL to be applied in complex tasks like robotics and game-playing. Transfer learning has gained prominence as a way to leverage pre-trained models and transfer their learned knowledge to new tasks or domains. Researchers such as [13] proposed Universal Language Model Fine-tuning (ULMFiT), which significantly improved natural language processing tasks with limited labeled data. Transfer learning has also been successful in computer vision, where models pre-trained on large datasets like ImageNet have been fine-tuned for specific tasks. Limitations and Challenges in AI and DL:Researchers have extensively discussed the limitations and challenges associated with AI and DL. For instance, [14] highlighted the need for better understanding of generalization and the trade-offs between optimization and generalization in DL models. They also emphasized the importance of interpretability and the development of methods to make DL models more transparent. Other challenges include the need for more robust training techniques, addressing bias and fairness issues, and handling large-scale deployment of DL models. The related work in the field of AI based on ML and DL demonstrates the wide range of techniques and models that have been developed. Supervised learning, unsupervised learning, reinforcement learning, and transfer learning have all seen significant advancements, enabling AI systems to tackle complex tasks and domains. However, challenges remain, such as the need for better generalization, interpretability, and addressing bias and fairness issues. Continued research and innovation in these areas will further advance the field of AI and its applications.

2. AI AND ML TECHNOLOGIES CLASSIFICATION

As per the definition provided in reference [15], artificial intelligence refers to the ability of a computer-controlled robot or digital computer to perform tasks that are commonly associated with intelligent entities. Artificial intelligence (AI) encompasses software and hardware

European Journal of Interdisciplinary Research and Development
Volume-17 July 2023
Website: www.ejird.journalspark.org ISSN (E): 2720-5746
methodologies that imitate or replicate human cognitive processes and actions. Artificial intelligence (AI) is categorized into weak AI, strong AI, or general artificial intelligence based on its level of intelligence in comparison to that of a human. This classification is established in literature [16] and is determined by the system's degree of intelligence [17, 18]. Contemporary pragmatic implementations employ artificial intelligence that is categorized as weak or soft to effectively tackle specific problems with a satisfactory level of precision. This study [16] centers on the development of artificial intelligence that possesses both robustness and versatility.
Artificial Intelligence (AI) is comprised of several noteworthy scientific fields, such as machine learning, natural language processing (NLP), text and speech synthesis, computer vision, robotics, planning, and expert systems. Figure 2 illustrates the domains of AI, as created by the authors through the utilization of sources. The preponderance of artificial intelligence (AI) applications are founded upon machine learning methodologies, which operationalize the fundamental principle of AI. Machine learning (ML) is utilized to enhance the accuracy of speech recognition and speech emotion recognition. A diverse range of machine learning techniques are utilized in economic planning and manufacturing control [40]. As stated by reference, machine learning (ML) is a powerful tool for data analysis that can be applied in various specialized systems. According to recent research, machine learning is currently considered a crucial field of study within the realm of robotics [18-20]. Frequently, machine learning is employed to address scientific and practical problems. The evaluation of the applicability conditions of machine learning (ML) as described in reference and the potential of deep learning as discussed in reference are considered for addressing challenges in the domain of chemistry [21].

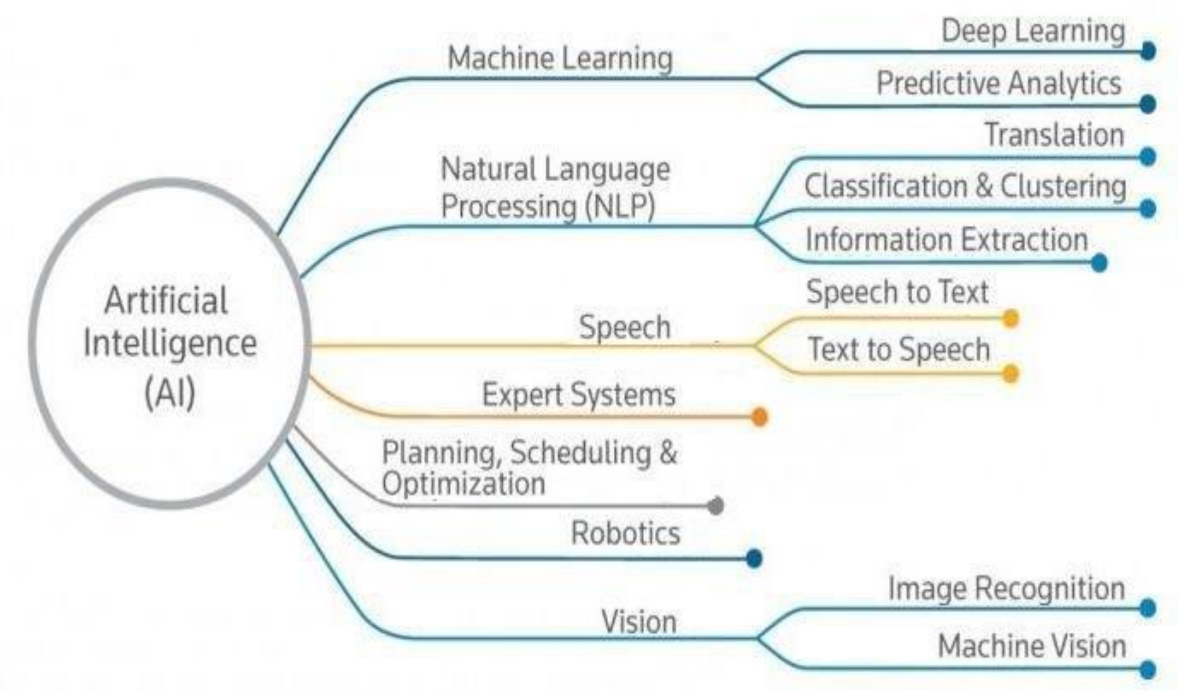

FIGURE 2. - **Artificial intelligence subdivisions. Author-generated content is the source.[22]**

The concept of "transfer learning" (TF) is a commonly employed term within the discourse of deep learning (DL). The concept of TF [22], refers to the phenomenon where a learner in a particular domain benefits from the transfer of information from a related domain. Both classical and contemporary machine learning , both classical and contemporary, can be categorized based on certain conditions, as illustrated in Figure 3 [23]. The traditional supervised learning (SL) models comprise (k-NN) [24], logistic regression [25], decision trees (DT), support vector machine (SVM) [26], as well as ANN) [27]. It should be noted that this list is not intended to be comprehensive. K-means and PCA, or principal component analysis, are considered as conventional UL models [28].

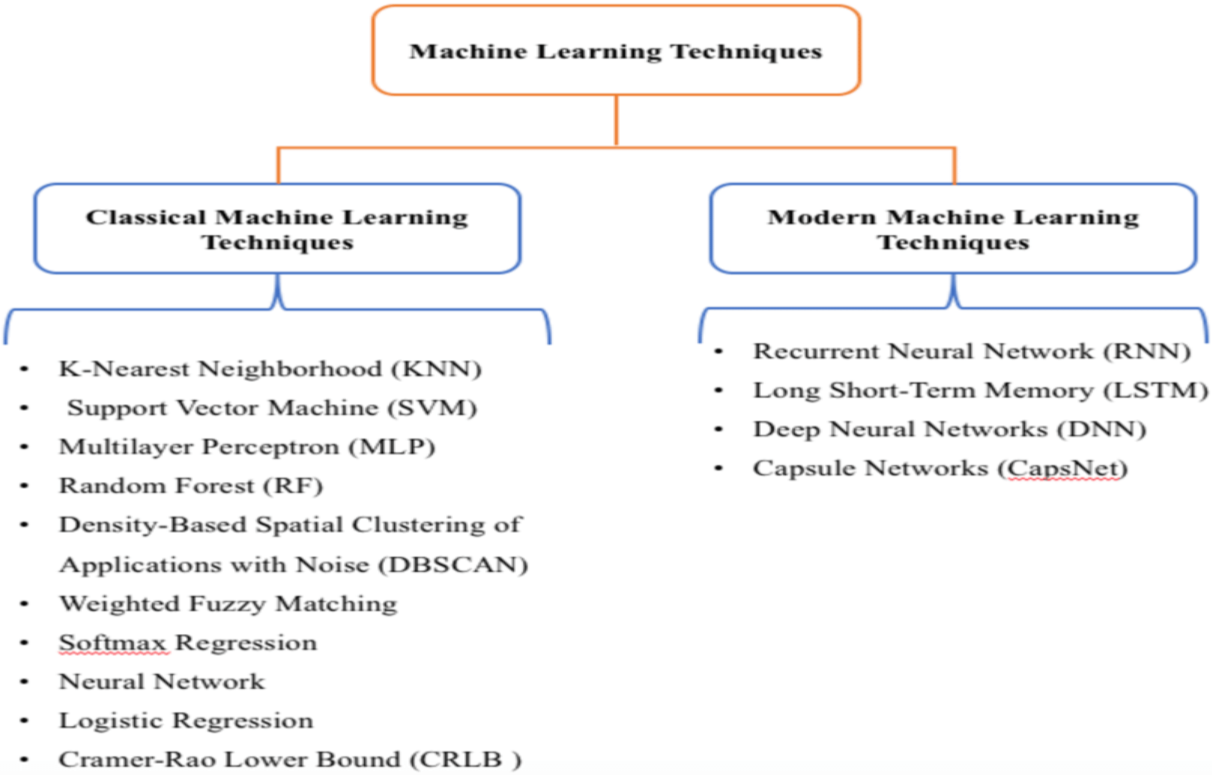

FIGURE 3. - **Classic and current ML models. Source: the writers made it up [29].**

According to recent research, deep learning has exhibited the most rapid expansion among subfields of artificial intelligence [29]. Deep Learning (DL) is a collection of methodologies that utilize deep neural networks, which are networks that consist of two or more hidden layers. The primary benefit of deep architectures pertains to their capacity to address tasks through the end-to-end approach. The utilization of a signal or image vector as the input for the network enables the network to independently recognize the patterns between the input vector as well as the target variable, thereby diminishing the necessity for preliminary data processing. The network performs the arduous and complex task of detecting salient features. This particular attribute of the network substantially streamlines the tasks of the researcher. Nonetheless, the aforementioned advantages can solely be observed when an ample amount of training data is available, and a neural network architecture is chosen appropriately. There exist three fundamental types of architecture among the numerous available ones [30]. The following adjusted models are based on these three fundamental architecture types (refer to Figure 4). Like

(FFNN, Recurrent neural network (RNN) , Convolutional neural network (CNN), Hybrid architectures, which combine elements of 1, 2, and 3 fundamental architectures, such as Siamese networks and transformers).

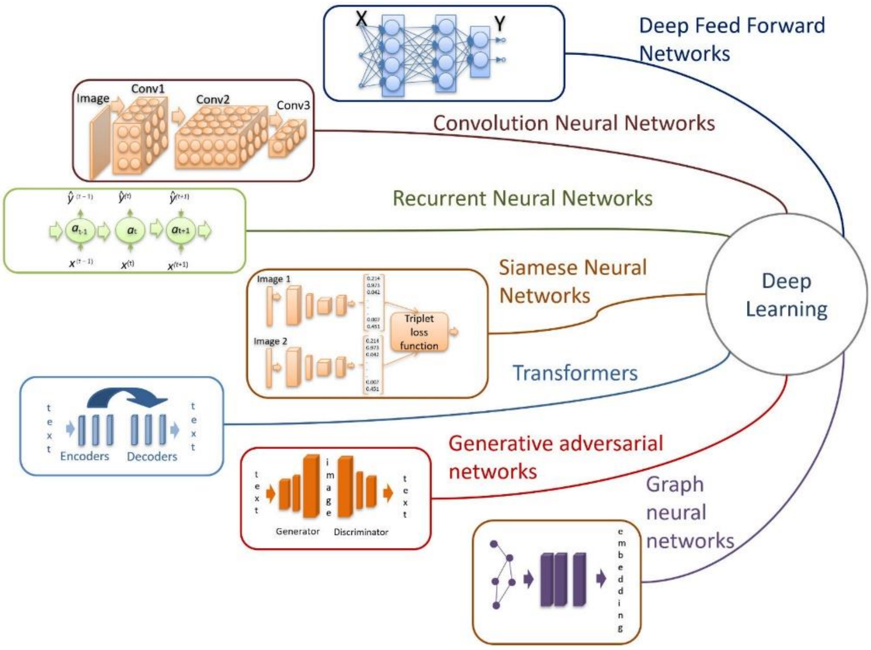

FIGURE 4. - **Deep Networks (DN).**

3. LIMITATIONS AND CHALLENGES OF AI AND ML APPLICATIONS

The adoption of artificial intelligence shows great promise. Artificial intelligence (AI) exhibits potential economic implications. [24] estimates a 200-billion-euro economic impact on European health care. It saves time and lives. References [16,17] provide an analysis of the implementation of artificial intelligence (AI) across various economic sectors. According to estimates from scholarly sources [17,25], the implementation of artificial intelligence (AI) has proven advantageous in the fields of commerce, logistics, automated production, and finance. High-tech products have the biggest impact (up to 10% profit growth). As a result, developed nations tend to experience a greater economic impact due to their production of high-tech goods in contrast to resource-dependent economies. Approximately 25% of Kazakhstan's gross domestic product (GDP) is derived from the activities of resource extraction, processing, and transportation, as reported in reference [18]. Approximately 70-75% of the exports are attributed to primary products. According to recent statistics [19], a mere 1% of enterprises can be classified as high-tech, while new items account for 1.6% of the GDP. It is projected that the growth of gross domestic product (GDP) in relation to artificial intelligence (AI) will range from 1.5% to 2%.Notwithstanding, there exist specific obstacles that, once surmounted, unlock novel prospects for the implementation of artificial intelligence in manufacturing and technological advancement.

Diverse categories of constraints have been recognized by the scientific community, encompassing organizational limitations [31], personnel-related constraints such as reluctance towards emerging technologies (particularly, anxiety regarding AI) and a scarcity of data scientists, data-related hurdles such as data quality and the management of substantial data volumes [32]. Additionally, they also encompass the presence of prejudices within data and constraints posed by technological capabilities. Furthermore, the authors draw attention to apprehensions pertaining to the opaque nature of specific technologies, as well as issues surrounding transparency and predictability. Additional concerns encompass the possible amplification of socioeconomic disparities and inequities, the ramifications for the economies of emerging nations, workforce displacement and substitution, matters of trust and acceptance, ethical and moral implications, and legal and regulatory frameworks [33].

1. A data provided is inadequate.
2. The variability of tissue or organ samples.
3. Issues related to non-binary classification.
4. The utilization of deep learning models is typically limited to smaller image sizes such as 608 x 608 for Yolo and 224 x 224 for VGG16, despite the availability of larger image sizes such as 50,000 x 50,000.
5. The Turing test presents a dilemma. The ultimate evaluation is conducted by an individual, which may not invariably be feasible.
6. The weak AI is oriented towards solving a single task, which results in increased training complexity and the emergence of the associativity problem as mentioned below.
7. The utilization of AI-based solutions incurs significant expenses due to the high computational costs involved.
8. Computer vision systems are unstable and susceptible to noise in medical diagnostics.
9. The absence of clarity as well as comprehensibility.
10. Challenges associated with the practical implementation of artificial intelligence. The challenges encountered in the Watson Health initiative [34] are linked to the intricacy of its implementation, limited trust in the outcomes, and elevated expenses.

At [35] shows that strong artificial intelligence makes associativity problematic. Current AI systems cannot meaningfully connect their findings to the real world. The unfunctional attribute of artificial intelligence (AI) systems renders them proficient in accomplishing designated tasks, yet incapable of generalizing the solution to analogous assignments. According to the study referenced as [36], it is recommended to explore novel deep neural network structures that can be utilized for the purpose of computer vision applications on board unmanned aerial vehicles. In order to process multispectral data, it is necessary to prepare datasets [37]. The implementation of Industrial AI necessitates the utilization of superior data, robust and verified ML models, cyber-infrastructure, distant operations, cybersecurity measures, privacy safeguards, and 5G technologies, as stated in source [38]. An issue exists regarding the reliability of data and the credibility of outcomes generated by artificial intelligence operations within the financial industry [39]. After conducting a thorough analysis of the existing literature, it is feasible to identify a set of concerns related to artificial intelligence (AI) technology. These concerns can be classified into two broad categories, namely external challenges and internal constraints that are inherent in the present state of AI technology (as illustrated in Figure 5).

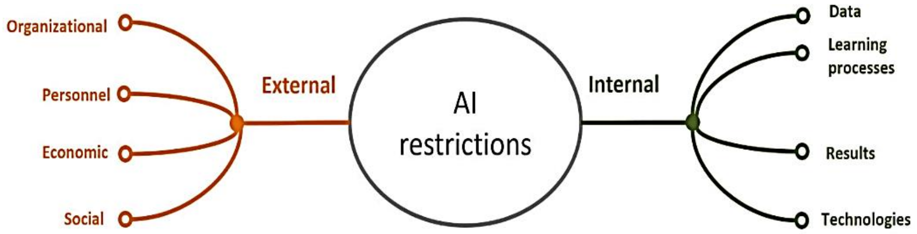

FIGURE 5. - Constraints impeding the economic implementation of AI technologies.

Tables 1 and 2 explain the existing limitations of AI technologies. Engineering and non-engineering specialists typically study Table 1's external AI issues. These limits can affect AI deployment and applications at all levels, from the government to a single department. Due to their intimate relationship, these problems require sophisticated solutions. Social limits, like ethical, moral, as well as legal problems, as well as organizational limitations, like lack of AI adoption plan as well as poor technology infrastructure, are multidimensional complex problems. These restrictions should be national strategies in many circumstances. One of the first recommendations for governments in the EU Ethics Guidelines for Trustworthy AI [40] is to provide an enabling environment for effective AI., the infrastructure of AI is crucial to implementing such techniques. This infrastructure is limited by technologies and external factors (see Table 2). First, data collecting, safety, and cybersecurity. Infrastructure development can also be decided by one company or academic institution. The government and each organization should address personnel issues.

The limitations of personnel are a result of several obstacles, including inadequate expertise, insufficient management support, and a society that is not fully immersed in the interests and practicalities of artificial intelligence. The education of personnel in the potential applications of artificial intelligence may commence during secondary education, a responsibility that falls under the purview of the government. The integration of AI components in web-based instructional programs enhances the accessibility and affordability of education, while concurrently elevating the standard of education and augmenting employment prospects. Economic constraints represent a prominent form of external limitations. The correlation between advancements in economic development and the level of readiness for artificial intelligence has been subject to scholarly investigation [41].

Table 1 . - External Al restrictions.

Governmental	Staff	Economical	Social Studies
1. The absence of a well-defined plan for the implementation of artificial intelligence. 2. Disjointed pieces of functionality that prevent AI from being used cohesively. 3. A failure of leadership and dedication to advance the state of AI. 4. Poor state of technology. 5. Data collecting challenges and little value.	1. Lack of comfort with novelty and innovation. 2. Lack of available skilled workers.	1. The hefty price tag associated with AI-based options. 2. not enough is ready for actual use. 3. economic inequality and the yawning wealth disparity. 4. the economies of developing nations	1. The outsourcing and automation of jobs. 2. Confidence and taking in 3. Moral and ethical concerns. 4. Policy concerns and legal matters

European Journal of Interdisciplinary Research and Development
Volume-17 July 2023
Website: www.ejird.journalspark.org ISSN (E): 2720-5746

Table 2 . - . Internal restrictions of AI technology

Data collecting	Learning Procedure	Outcomes	Practical application
1. The research process is hampered by the challenges of data collecting and analysis. 2. Data must be abundant. 3. Data inadequacy and difficult annotation. 4. Privacy, bias, and data security matter.	3. Learning is slow. 4. Large computing capacities are needed. 5. No major image processing technologies.	1. Absence of clarity and interpretability	2. Noise makes previous solutions unstable. 3. Modern machine learning models lack associativity and multitasking. 4. Modern machine learning models lack associativity and multitasking. 5. Industrial AI/ML applications require cyber infrastructure.

The authors express their acknowledgement of the specific limitations that are inherent in economies that rely on natural resources, particularly in relation to the broader constraints that exist within the domain of artificial intelligence. As previously stated, economies that rely on natural resources as their primary source of income tend to have a GDP that is heavily influenced by the extraction and refinement of these resources. These methodologies employ technologies that have been imported. The facilitation of technology transfer from foreign nations may lead to a lack of emphasis on domestic innovation in technology within the economies in question.

Many nations frequently encounter deficiencies in their information and communication technology (ICT) infrastructure, human resources, and regulatory structure, which impede their ability to gather sufficient data for the development of artificial intelligence (AI) algorithms. Frequently, available data remains underutilized due to tardiness or non-receipt, non-digitization, or inadequate granularity for on-site decision-making and inventive pursuits. Therefore, it is advisable to restrict the economic advantages derived from artificial intelligence. The utilization of high-tech production techniques has been observed to enhance the effectiveness of AI and ML technology, as noted in reference [17]. The domains of agriculture, healthcare, and education have witnessed significant advancements owing to the integration of big data and artificial intelligence.

4. DISCUSSION

Artificial intelligence (AI) exhibits considerable potential, however, its practical implementation in production and services is frequently hindered by current technological limitations. It is imperative to conduct an analysis of the internal challenges posed by AI technology and assess the feasibility of surmounting these restrictions.

1. The process of generating data for the purpose of training deep machine learning models. The utilization of comprehensive and high-quality data sets can effectively address a multitude of challenges in the field of deep learning. Image datasets that have been annotated and categorized, such as ImageNet, Open Images, COCO Dataset, and FaceNet, are frequently employed to tackle computer vision problems. Notwithstanding its widespread usage, the conventional DS may prove insufficient in addressing certain complexities, such as the task of recognizing objects. According to synthetic data sets can be constructed using 3D graphic

editors, game engines, and environments as a solution to address the lack of data in computer vision. The training program for unmanned vehicles entails the utilization of DS, as [30]. Synthetic datasets are employed in diverse domains [25]. The aforementioned entities were produced through the utilization of generative adversarial networks, as documented in reference [20]. The study presented in reference [31] offers a thorough assessment of techniques for generating synthetic datasets.

2. Increased speed of observation. As per the transfer learning paradigm, leveraging pre-trained models can expedite the learning process in scenarios where the domain and task at hand bear resemblance to the pre-existing solutions [20-25]. It is possible to increase the depth of a neural network by adding layers after training it on a substantial dataset. In the final phase of training, the layers are fine-tuned on a limited and specific dataset. The remaining layers are "static" as well as their weights remain invariant. The initial trained neural network retains the fundamental characteristics of a particular data set category, such as facial images, landscapes, or vocal recordings. Subsequent layers of the network are designed to concentrate on the distinctive attributes of a specialized data set. The utilization of transfer learning expedites the process of acquiring knowledge and reduces the hardware requirements.

3. Elucidating the outcomes of a machine learning model. The field of AI has recently achieved success owing to the swift progress in machine learning technology. Nonetheless, the utilization of "black box" learning poses certain risks. In contrast to conventional machine learning techniques such as decision trees, non-linear classification as well as deep learning models are characterized by a lack of transparency, rendering it challenging to comprehend the underlying rationale behind algorithmic decision-making. The hindrance of AI's widespread adoption in healthcare, banking, as well as other industries has been documented in scholarly literature [32-36].

4. The complex nature of advanced machine learning models is frequently denoted as "black boxes" due to their inscrutable characteristics that obscure their internal mechanisms. The examination of the influence of input parameters on the ultimate outcome leads to the conversion of the "black " into a "white" or "grey" . Presently, there exist four distinct categories of explanation approaches [35], namely explanation target, explanation scope, model type, and data type employed for the training of the machine learning model (refer to Figure 6). It is commonly preferred that the interpreter remains impartial and provides both the worldwide and specific interpretations. The challenges at hand are partially addressed by the utilization of the Interpretable Model-Agnostic (LIME) and SHapley Additive exPlanations (SHAP) techniques. Models that exhibit substantial attribute correlation and complexity can pose challenges in their application due to the linear nature of interpretation (LIME) and the intricate nature of calculations (SHAP), as noted in reference [28].

Clear parameters allow interpretation of their effects. Such an interpretation would be meaningless if semantically unclear parameters were uses. The difficulties outlined above must be solved to implement AI&ML technology in the economy. Possible research directions are listed in Table 3 (a,b). Explainable machine learning models are widely adopted in various industries due to their favorable D1 and D2 values. Elevated D2 levels are also observed in the sectors of warehousing, merchandising, manufacturing, transportation, advanced farming, and data analysis. The significant increase in the number of lead articles in diverse scientific fields, surpassing a volume of 1000, including but not limited to "deep learning," agricultural farming with precision, supply-chain management, transportation, healthcare, and manufacturing, is a remarkable observation (as depicted in Figure 6).

The inference that can be drawn is that these industries are poised to innovate novel technologies utilizing deep learning models. AI technology's economic efficiency will grow if at least some of its underlying issues are resolved. AI's economic impact depends on overcoming the aforesaid limits, The availability of research resources and the prevailing conditions of a nation are factors that can impact research outcomes. It is noteworthy that Kazakhstan's spending on research and development accounted for 0.125% of its GDP in 2018.

Table 3.a. - **Directions of research oriented towards overcoming the limitations of AI&ML usage.**

	Overcoming the External Limitations of AI&ML
Administrative	Unifying data set generation procedures and developing data accumulation and use regulations and technologies.
Personnel	specialized training and explanation in the applied specialized settings
Economic	Creation of unified solutions applicable in various sectors.
Social	AI-driven economic modeling, helping explainable AI as well as social science research. Artificial emotional intelligence can improve human-machine interaction. Interaction and customised AI in medicine should detect patients' preferences, support patients (as well as their families) in taking part in the treatment process, customize "general" therapy strategies, plus personalize information about patients.

Table 3.b. - **Directions of research oriented towards overcoming the limitations of AI&ML usage.**

	The Internal Limitations of AI&ML
Data	Data markup and collection unified. Data set creation for AI&ML applications .AI&ML application
Learning procedures	Research in field to transfer procedures.
Outcomes	Research into computer power and new method. Development of machine learning model interpretation methods and simplified interaction with application specialists. Similar models are for professionals only. Machine learning models for drone applications. Strong or general AI research on machine learning model stability.
Technologies	Human-machine symbiosis research aims to augment human intelligence rather than replace it.

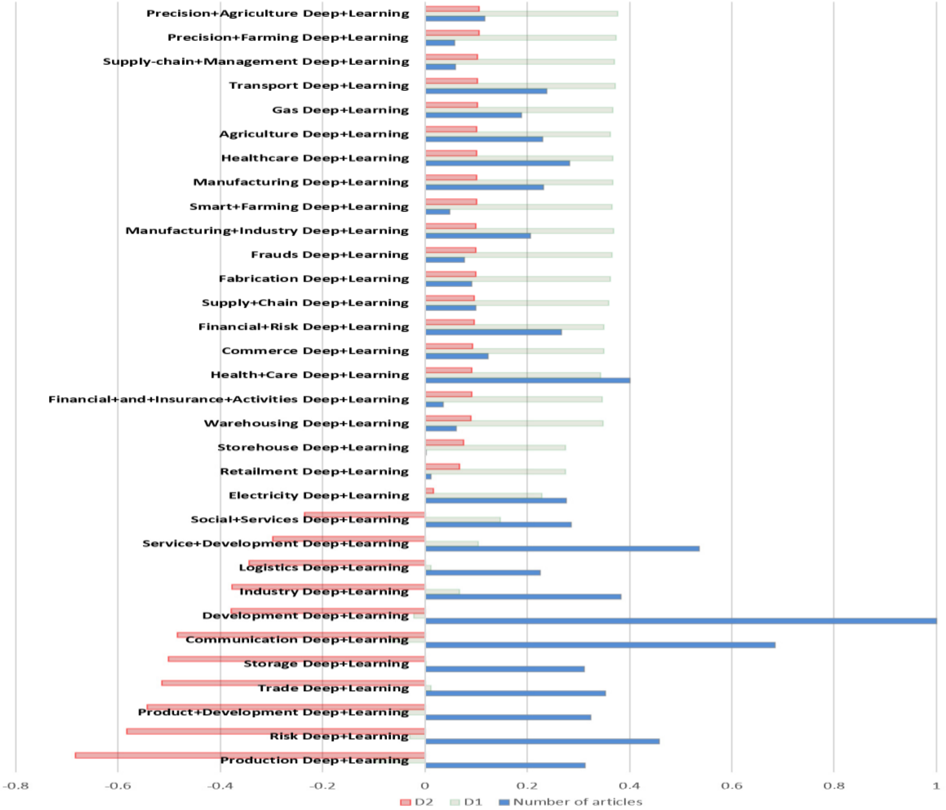

FIGURE 6. - The rate of growth D1 and the rate of growth D2 of scientific papers in the fields where deep learning has been used.

5. CONCLUSIONS

In the realm of artificial intelligence, deep learning is the area that is developing the quickest at the moment. There have been numerous reports of new discoveries and possible uses for proposed networks. Text recognition, recognition of speech, recognition of handwriting, image transformation as well as styling, as well as time sequence processing are just few of the many activities that are studied and implemented in this field of study and application. However, there are obstacles to implementing AI&ML, both inherent to the technologies and the social and economic context, which may not be ready for the rapid changes. The goal of this study is to begin to standardize AI's several subfields. Our group has characterized the obstacles that prevent the widespread use of AI technology, especially in resource-based economies. External factors, such as the structure of an enterprise's operations as well as information collection, and psychological problems stemming from a lack of understanding of the operational processes of machine learning algorithms, limit the use of AI and ML techniques. The scientific community works to overcome technological barriers including a lack of data for deep learning models, improve AI models, and speed up the learning process. The number of scholarly works being published annually is rising. In the not-too-distant future, we hope to have conquered our technological obstacles. To speed up the learning process, improve the clarity of ML results, and generate datasets, numerous approaches have been developed and deployed. Most AI programs still have serious shortcomings that need fixing before they can be widely used. They are crucial in fields where AI could have a major impact on the economy and society. Soil quality as well as salinity assessments, as well as increases in agricultural output, could benefit greatly from the combination of remote sensing as well as machine learning approaches. Future research efforts, in our opinion, should focus on creating comprehensive and easily accessible data sets, incorporating existing technologies, and developing task-specific methodologies in a wide range of fields, including mining, transportation, business, finance, healthcare, and more.

REFERENCES

1. Liakos, K.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: A review. Sensors 2018, 18, 2674. [CrossRef]
2. Ali, J.M.; Hussain, M.A.; Tade, M.O.; Zhang, J. Artificial intelligence techniques applied as estimator in chemical process systems A literature survey. Expert Syst. Appl. 2015, 42, 5915–5931.
3. Q. A. Xu, V. Chang, and C. Jayne, “A systematic review of social media-based sentiment analysis: Emerging trends and challenges,” Decision Analytics Journal, vol. 3, p. 100073, Jun. 2022, doi: 10.1016/j.dajour.2022.100073.
4. A. Catovic, C. Cartwright, Y. T. Gebreyesus, and S. Ferlin, “Linnaeus: A highly reusable and adaptable ML based log classification pipeline,” 2021 IEEE/ACM 1st Workshop on AI Engineering - Software Engineering for AI (WAIN), May 2021, doi: 10.1109/wain52551.2021.00008.
5. Jain, A.K.; Murty, M.N.; Flynn, P.J. Data clustering: A review. ACM Comput. Surv. 1999, 31, 264–323. [CrossRef]
6. S. Shrestha and S. Das, “Exploring gender biases in ML and AI academic research through systematic literature review,” Frontiers in Artificial Intelligence, vol. 5, Oct. 2022, doi: 10.3389/frai.2022.976838.
7. “Types and varieties,” Australian Kin Classification, pp. 39–87, Sep. 1978, doi: 10.1017/cbo9780511557590.004.
8. D. C. Verma, A. Verma, and U. Mangla, “Addressing the Limitations of AI/ML in creating Cognitive Solutions,” 2021 IEEE Third International Conference on Cognitive Machine Intelligence (CogMI), Dec. 2021, doi: 10.1109/cogmi52975.2021.00033.
9. Barbakh, W.A.; Wu, Y.; Fyfe, C. Review of clustering algorithms. In Non-Standard Parameter Adaptation for Exploratory Data Analysis; Springer: Berlin/Heidelberg, Germany, 2009; pp. 7–28.
10. M. Jiayi Tao, “Potential limitations of the Brooker Classification for Heterotopic Ossifications,” Apr. 2018, doi: 10.26226/morressier.5ade45fdd462b8029238e703.
11. Shikha, M. Agrawal, M. A. Anwar, and D. Sethia, “Stacked Sparse Autoencoder and Machine Learning Based Anxiety Classification Using EEG Signals,” The First International Conference on AI-ML-Systems, Oct. 2021, doi: 10.1145/3486001.3486227.
12. “AI/ML for Mission Processing Onboard Satellites,” Jan. 2022, doi: 10.2514/6.2022-1472.vid.
13. P. Durko, “Advanced Testing of Physical Security Systems through AI/ML,” Advanced Testing of Physical Security Systems through AI/ML, Oct. 2021, doi: 10.2172/1831133.

14. Simonyan, K.; Zisserman, A. Very deep convolutional networks for large-scale image recognition. arXiv 2014, arXiv:1409.1556.
15. D. C. Verma, A. Verma, and U. Mangla, “Addressing the Limitations of AI/ML in creating Cognitive Solutions,” 2021 IEEE Third International Conference on Cognitive Machine Intelligence (CogMI), Dec. 2021, doi: 10.1109/cogmi52975.2021.00033.
16. U. Bhatt, D. Iyyani, K. Jani, and S. Mali, “Troll-Detection Systems Limitations of Troll Detection Systems and AI/ML Anti-Trolling Solution,” 2018 3rd International Conference for Convergence in Technology (I2CT), Apr. 2018, doi: 10.1109/i2ct.2018.8529342.
17. Cortes, C.; Vapnik, V. Support-vector networks. Mach. Learn. 1995, 20, 273–297. [CrossRef]
18. Kumar, D.P.; Amgoth, T.; Annavarapu, C.S.R. Machine learning algorithms for wireless sensor networks: A survey. Inf. Fusion 2019, 49, 1–25.
19. V. P. S. Rallabandi and K. Seetharaman, “Class Imbalance ML Methods for Classification of Dementia Stage: Kurtosis Fractional Anisotropy: ML-based classification of dementia stage (paper subtitle),” 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), May 2021, doi: 10.1109/iciccs51141.2021.9432112.
20. S. Lee, “AI-Based CYBERSECURITY: Benefits and Limitations,” J-Institute, vol. 6, no. 1, pp. 18–28, Mar. 2021, doi: 10.22471/ai.2021.6.1.18.
21. Goldberg, Y. A primer on neural network models for natural language processing. J. Artif. Intell. Res. 2016, 57, 345–420. [CrossRef]
22. V. P. S. Rallabandi and K. Seetharaman, “Class Imbalance ML Methods for Classification of Dementia Stage: Kurtosis Fractional Anisotropy: ML-based classification of dementia stage (paper subtitle),” 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), May 2021, doi: 10.1109/iciccs51141.2021.9432112.
23. “Framework for Artificial Intelligence (AI) Systems Using Machine Learning (ML)”, doi: 10.3403/30374632.
24. “Machine Learning Based News Text Classification,” Machine Learning Theory and Practice, vol. 1, no. 1, Mar. 2020, doi: 10.38007/ml.2020.010103.
25. MacQueen, J. Some methods for classification and analysis of multivariate observations. In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, Auckland, CA, USA, 7 January 1967; pp. 281–297.
26. “Proceedings of the Workshop on Network Meets AI & ML,” Aug. 2020, doi: 10.1145/3405671.
27. E. Hechler, M. Weihrauch, and Y. Wu, “Relevant ML and DL Concepts,” Data Fabric and Data Mesh Approaches with AI, pp. 123–146, 2023, doi: 10.1007/978-1-4842-9253-2_6.
28. Weiss, K.; Khoshgoftaar, T.M.; Wang, D. A survey of transfer learning. J. Big Data 2016, 3, 1–40. [CrossRef]
29. F. Tango and M. Botta, “ML Techniques for the Classification of Car-Following Maneuver,” Lecture Notes in Computer Science, pp. 395–404, 2009, doi: 10.1007/978-3-642-10291-2_40.
30. S. Haider, A. Mahmood, S. Khatoon, M. Alshamari, and M. T. Afzal, “Automatic Classification of Eyewitness Messages for Disaster Events Using Linguistic Rules and

ML/AI Approaches," Applied Sciences, vol. 12, no. 19, p. 9953, Oct. 2022, doi: 10.3390/app12199953.

31. "The three biggest trends in AI and ML right now," Nov/Dec 2019, Oct. 2019, doi: 10.1287/lytx.2019.06.02.
32. M. Shah, A. Kshirsagar, and J. Panchal, "Finance with ML and AI," Applications of Artificial Intelligence (AI) and Machine Learning (ML) in the Petroleum Industry, pp. 91–101, Jul. 2022, doi: 10.1201/9781003279532-7.
33. A. Dziatkovskii, "THE ERGONOMIC EFFECT OF AI & ML IN EDUCATION," THE ERGONOMIC EFFECT OF AI & ML IN EDUCATION, 2023, doi: 10.46916/26042023-1-978-5-00174-960-8.
34. Sadovskaya, L.L.; Guskov, A.E.; Kosyakov, D.V.; Mukhamediev, R.I. Natural language text processing: A review of publications. Artif. Intell. Decis. Mak. 2021, 95–115. [CrossRef]
35. M. Shah, A. Kshirsagar, and J. Panchal, "Safety and maintenance with AI and ML," Applications of Artificial Intelligence (AI) and Machine Learning (ML) in the Petroleum Industry, pp. 79–89, Jul. 2022, doi: 10.1201/9781003279532-6.
36. Mukhamediev, R.I.; Kuchin, Y.; Amirgaliyev, Y.; Yunicheva, N.; Muhamedijeva, E. Estimation of Filtration Properties of Host Rocks in Sandstone-Type Uranium Deposits Using Machine Learning Methods. IEEE Access 2022, 10, 18855–18872. [CrossRef]
37. Dudani, S.A. The distance-weighted k-nearest-neighbor rule. IEEE Trans. Syst. Man Cybern. 1976, 4, 325–327. [CrossRef]
38. Nassif, A.B.; Shahin, I.; Attili, I.; Azzeh, M.; Shaalan, K. Speech recognition using deep neural networks: A systematic review. IEEE Access 2019, 7, 19143–19165. [CrossRef]
39. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. Nature 2015, 521, 436–444. [CrossRef]
40. Yu, H.-F.; Huang, F.-L.; Lin, C.-J. Dual coordinate descent methods for logistic regression and maximum entropy models. Mach. Learn. 2011, 85, 41–75. [CrossRef]
41. Zhang, G.P. Neural networks for classification: A survey. IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.) 2000, 30, 451–462. [CrossRef]