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ANALYSIS ON EXPLORATIONS IN ARTITIFICAL INTELLIGENCE AND MACHINE LEARNING

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ABSTRACT

Intelligent data processing, natural language processing, autonomous vehicles, and robotics are just a few of the many key applications and areas of research that benefit from the study of artificial intelligence. Machine learning (ML) refers to a set of procedures and techniques used to solve the issues of categorization, clustering, and prediction at the heart of AI. Artificial intelligence and machine learning's potential in the real world is bright. As a result, there is a lot of study being done in this field. But at the moment, AI's more intensive social use and its industrial uses are still not commonplace. Both AI itself (internal problems) and society as a whole (external problems) must be taken into account while attempting to tackle the difficulties of ubiquitous AI applications. Priorities for expanding the use of AI in industry and society can be determined after giving this issue careful thought. This article identifies and discusses some of the obstacles to using artificial intelligence in resource-based economies and societies. Publications in the field form the basis for the systematic application of AI&ML technology. Through this methodical approach, we are able to define our organisational, human resources, societal, and technological bounds. This review article lays out the research priorities in AI and ML that will allow us to extend the range of AI&ML's applications and overcome some of its limitations.

Key words: Artificial Intelligence, Machine Learning, Social Technological applications.

1. INTRODUCTION

Automated reasoning, intelligent systems, knowledge representation, and game theory are just a few of the many fields that have benefited from AI during the past 60 years. Recent developments in computing power, the quantity of available data, and new algorithms, however, have shown that AI can play a key part in the digital transformation of society and so should be a priority for any nation. Researchers have therefore focused heavily on creating innovative AI methods for use in numerous important areas, including cyber security, e-health, military applications, and smart cities.

Artificial intelligence research is developed and discussed in the scientific community (AI). Research in this area takes into account both the theoretical foundations of AI systems and their practical implementations across a wide range of societal domains. Machine learning (ML) is a set of techniques frequently employed in AI that enable the prediction of new data qualities using the properties already revealed in the training data. There is a subset of machine learning known as "deep learning" (DL). Recently, there has been increased attention from the research community on this matter. The vast quantities of theses and dissertations preserved in academic libraries attest to this. In Figure 1, Scopus data on reviews in the areas of AI, ML, and DL from 2000 to 2021 is displayed.

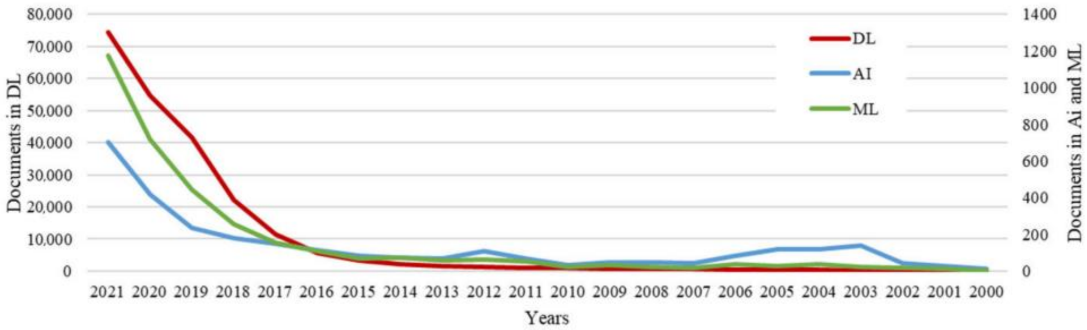

Figure 1. The number of review studies in Scopus that are about artificial intelligence, machine learning, and deep learning.

The use of AI techniques is widespread. The most often addressed applications in scientific literature are depicted in Figure 2. Studies in computer science, engineering, and mathematics [1,2] are often the basis for artificial intelligence, machine learning, and deep learning.

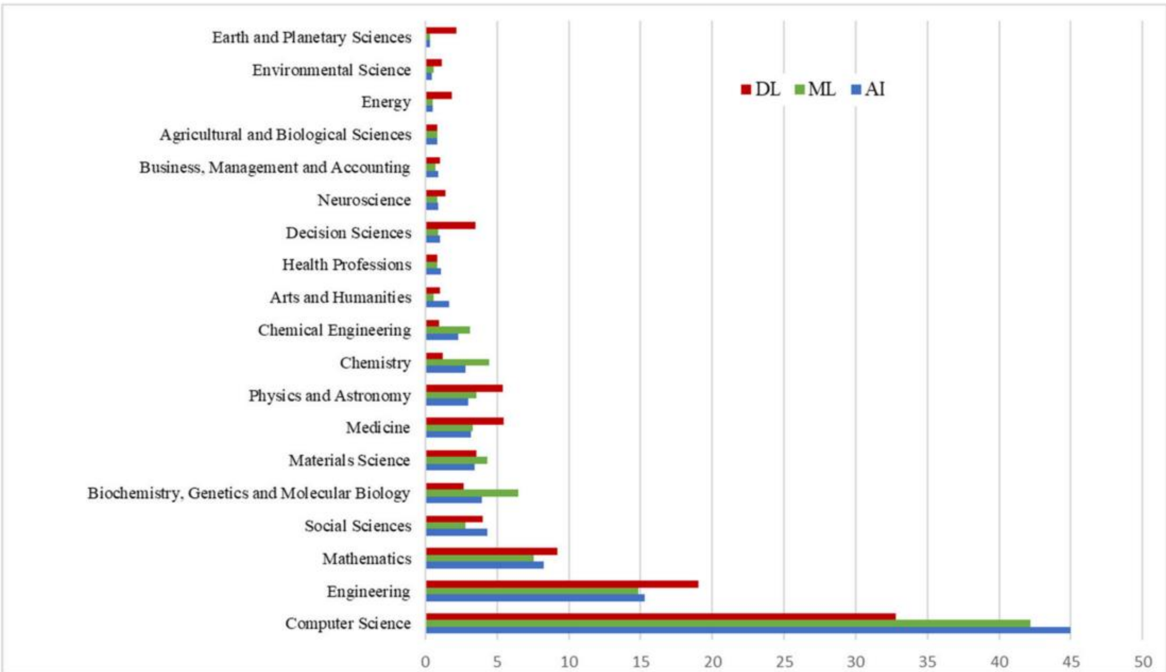

Figure 2. Reviews are ranked according to their usefulness in various fields (percentage).

Computer scientists investigate a varied set of issues in this field. Smart software and hardware, including image and signal processing, natural language processing, security, and data analysis rely on the findings of this research (for example, brain–computer interface). Data visualisation, machine learning, and AI are all used in these investigations. These techniques have proven effective in many other contexts besides computing. As can be seen in [3], there are far-reaching ramifications for business, logistics, automated production, and finance as a result of the implementation of AI.The authors of [4] also consider the potential applications of AI in the business world. Despite this, the majority of these articles concentrate on AI's prospective applications. By implementing AI and ML in more settings, we hope to solve some of the problems that have arisen as a result of their broad use. These issues can be recognised and researched by a rigorous analysis of AI and ML. The provided study opens up avenues for contemplation of the various forms of AI and ML, their interrelationships, and potential growth areas.

2. REVIEW OF LITERATURE

2.1 Artificial Intelligence and Machine Learning Technologies Classification

A digital computer or computer-controlled robot with artificial intelligence can "perform tasks traditionally associated with intelligent beings" [5]. Generally speaking, AI refers to the application of computational and mathematical methods to the problem of simulating human intelligence. Strong AI, often known as general artificial intelligence, is distinguished from weak AI in terms of how closely it mimics human intelligence. Today's practical applications rely on weak or soft AI because it can solve certain problems with an accuracy level sufficient for use in the real world. The goal of this study is to create AI that can be used for a wide variety of tasks and is very effective in its implementation [6].

There are many different subfields that fall under the umbrella of artificial intelligence. Some of these subfields include machine learning, natural language processing, speech and text synthesis, computer vision, robotics, planning, and expert systems. The artificial intelligence domains that the authors created with the available resources are displayed in Figure 3.

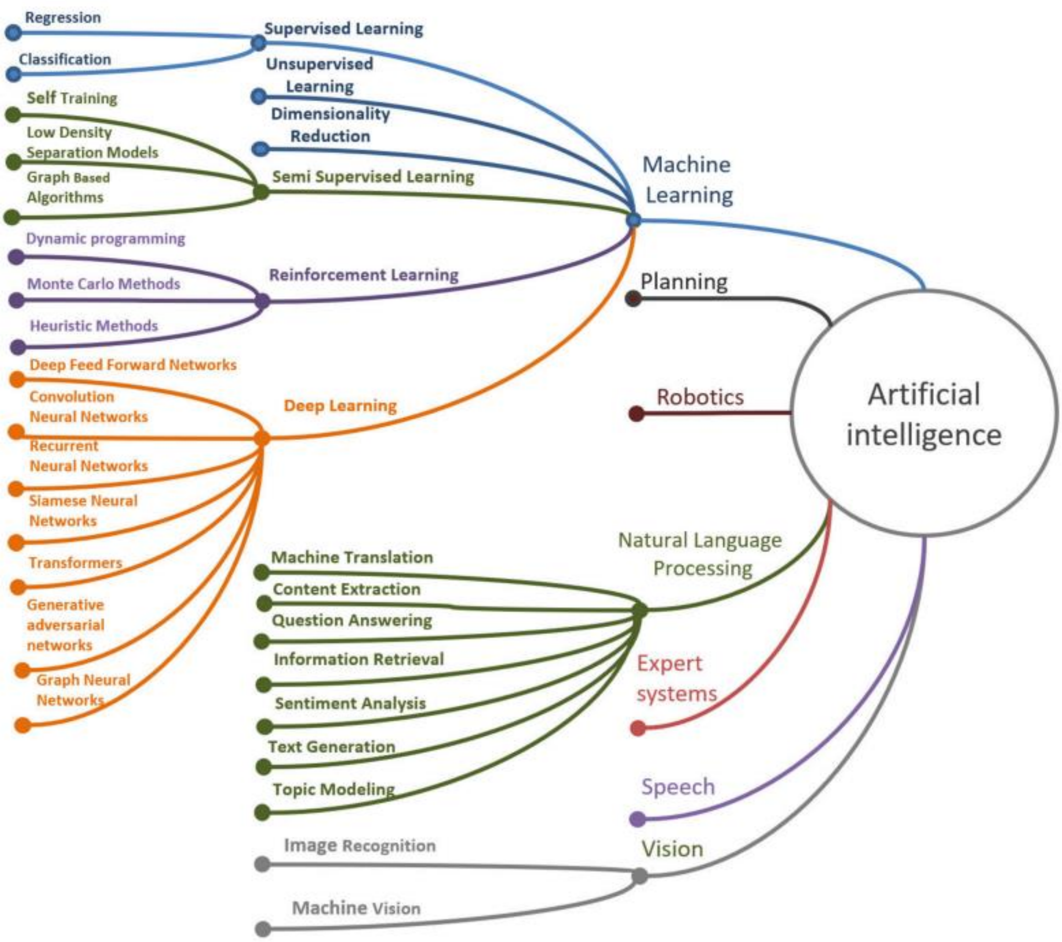

Figure 3. Subsections of artificial intelligence

Machine learning techniques are the backbone upon which the vast majority of AI applications are constructed; these techniques provide concrete form to the AI concept itself [7]. Artificial intelligence (AI) is used to enhance performance in areas such as voice emotion recognition. Economic forecasting and factory management both make use of ML techniques. Expert systems of all kinds can benefit from machine learning, as noted in ref. [8]. One of the most active fields of study in robotics nowadays is machine learning.

Both theoretical and practical issues in science and technology find frequent application for machine learning. For instance, in order to address issues in the field of chemistry, we evaluate the ML application criteria and the potential of deep learning. Medical imaging is just one of the many fields where ML has been put to use. Petrographic research, exploration, and mining predictions are only a few additional examples, along with astronomy, computational biology, agriculture, municipal economy and industry, building, modelling environmental and geo-ecological processes, and a few others. The discipline of natural language processing makes extensive use of ML, and it forms the backbone of current research [9].

2.2 Limitation and Difficulties in the AI and ML Application

The future of AI is bright, and it's expected to be used in many contexts. The potential financial impact of AI applications is widely regarded as promising. There will be a cost to the European healthcare system of almost 200 billion euros, as reported in [10]. Time is preserved, and more lives are spared as a result of this consequence. Refs. To [11] show the outcomes of AI implementation in different economic areas. Many businesses stand to gain considerably from the use of AI, with estimates ranging from $600 million to $800 million (USD) across retail ($400 billion), logistics ($400 billion), automated production ($300 billion), and banking ($300 billion) [12]. The impact is highest in high-tech goods (up to 10% of profit growth). Therefore, industrialised countries, which produce more high-tech items, feel a greater economic impact than resource-based economies. Kazakhstan's GDP is comprised, in part, of the activities involved in the mining, refining, and transport of its many natural resources [13]. 70%–75% of total exports are made up of primary goods. Only 1% of businesses are considered high-tech, despite the fact that innovative items account for 1.6% of GDP [14]. Thus, it is expected that the application of AI technology will lead to a 1.5-2% increase in GDP.

Associativity challenge in strong AI is discussed in the paper [15], which is defined as the restricted applicability of the results and the incapacity of present AI systems to link the conclusions to the real world. AI systems exacerbate this problem because they are limited to doing only the tasks for which they have been trained, and hence cannot independently apply the solution to similar tasks.

New deep neural network architectures are needed, according to research [16], for the specialised tasks of UAV computer vision. It also discusses the importance of preparing the data sets for specific uses, such as multispectral data processing.

Cyber-infrastructure (including remote operations, cybersecurity, privacy safeguards, and 5G technologies), as well as high-quality data and machine learning models that have undergone extensive testing, are also required for industrial AI [17].

Data synthesis is used for training machine learning models. It is impossible to solve many of deep learning's problems without a massive amount of high-quality data, sometimes known as a "data set" (DS). ImageNet [18], Open Images, the COCO Dataset, and FaceNet are some of the most popular labelled image databases used to solve computer vision challenges. Even the most popular DS would struggle to address every issue. For instance, their object recognition might be somewhat restricted. Data scarcity is a difficulty in computer vision, however it can be overcome by using a synthetic DS created on 3D graphic editors, game engines, and surroundings. More specifically, these DS are put to use in the education of unmanned vehicles. Other fields also make use of synthetic datasets. As of late, they've been generated using generative adversarial networks. In [19], we see a comprehensive analysis of the methods used to generate the simulated data sets.

3. EXPLORATION ON APPLICATIONS OF AI AND ML IN OIL AND GAS INDUSTRY

Systems for reservoir engineering, drilling engineering, production engineering, and oil field exploration are all part of the petroleum industry's toolbox. Plastics, solvents, fertilisers, insecticides, and pharmaceuticals all get their start from oil and gas (Anderson, 2017). Companies dependent on fossil fuels will need to invest in R&D to improve efficiency and expand capacity if the price of these fuels continues to grow. Oil fields produce more water than oil at the moment because of development and processes including water front arrival at the coast, channelling, coning, and water breakthrough.

As a result, extracting petroleum from this formation would be very expensive. Plus, no oil or gas company is interested in investing in very expensive engineering or equipment because the price of oil has not yet stabilised. The simplest method to cut costs while increasing output is to maximise cumulative extraction through efficient and clever technology, such as Inflow Control Devices (ICDs), Inflow Control Valves (ICVs), and downhole sensor systems. More effective management of huge oilfields calls for prompt decision making that takes into consideration the complexity of these operations and other factors. Through digitising instrumentation systems and fostering network-based information exchange, the Smart Oilfield will establish a comprehensive oilfield technological infrastructure to optimise the production process (Temizel et al., 2019)

It's now beyond reasonable doubt that the digital revolution has had far-reaching effects on the world's economy and society. Since its start, digital transformation has been clearly the "fourth industrial revolution," as seen by the proliferation of interconnected technologies that span the physical, digital, and biological realms, such as artificial intelligence (AI), robots, and driverless cars. The quick reaction times and strong ability for generalisation of artificial intelligence (AI) technologies are drawing a lot of interest (Evans, 2019).

For many reservoir engineering problems, there is encouraging evidence to suggest that machine learning can supplement or perhaps replace more traditional approaches (Anifowose et al., 2017). Researchers in several fields have turned to sophisticated machine-learning methods like Fuzzy Logic (FL), Artificial Neural Networks (ANN), Supporting Vector Machines (SVM), and Response Surface Models (RSM) to solve classification and regression issues (Ani et al., 2016). Reservoir engineers use a wide variety of supervised machine learning techniques. Evolutionary optimization methods like the Genetic Algorithm (GA) and Particle Swarm Optimization are frequently used in reservoir engineering (PSO).

Researchers could improve their ability to forecast the outcome of inverse scenarios by incorporating analytical methods that combine forward- and backward-looking AI models.

Predictive Gaussian proxy designs, Bayesian optimization, and numerical models of high-fidelity procedures were used in conjunction with AI to reorganise typical platform operations (Rana et al., 2018). New technology is used to address an issue with a retrofitted coal seam degasification scheme. The use of Bayesian theory to maximise efficiency. It has a wide range of distributional solutions for reservoir features that can be used to fit field data (Esmaili and Shahab, 2016).

Using a microstructured grid, the oil and gas businesses of the Gulf of Mexico have gathered data on the impacts of technological developments on oil and natural gas inspection. Sami and Ibrahim (2021) investigated three distinct machine learning techniques in order to better understand how to estimate bottom hole pressure in multiphase flowing conditions. Real-world information is used during the model's development and testing, all of which may be accessed through a publicly available literature database. The correctness of the method was assessed across various datasets to check the accuracy of the BHPs obtained using ML models and prove the usefulness of the study.

In order to forecast the rate of penetration in directional wells, Hazbeh et al. examined the accuracy and computing efficiency of machine learning algorithms (2021). The rock uniaxial strength features of the Iranina carbonate oil deposit were determined by Hassanvand et al. (2018) using a synthetic neural network. Priyanka et al. conducted a comprehensive assessment and analysis of the use of cloud-based smart grid technologies in the oil pipeline sensor network system (2021).

The oil and gas industry faces opportunities, difficulties, risks, and new developments that can be addressed with knowledge of block chain technology. Block chain technology will have several positive effects on the oil and gas business, including lowering transaction costs and increasing transparency and efficiency. The natural progression of blockchain technology in the oil and gas business would be to implement cross-chain, updated smart contracts and an injection of multidisciplinary knowledge (Lu et al., 2019). Casing drilling technology, cutting-edge innovations, enhanced oil recovery, synthetic, thermal, physical, chemical methods, Microbial Enhanced Oil Recovery (MOER), and water alternating gas (WAG) processes are just some of the areas where the block chain approach is making an impact in this industry.

4. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS IN SMART PRODUCTION

There is a need for creative ideas in smart production systems in order to boost product quality and durability while lowering manufacturing costs. New manufacturing paradigms [32] are set to emerge because of the I4.0 Key Enabling Technologies (IoT, sophisticated embedded systems, cloud computing, big data, cognitive systems, virtual and augmented reality) (AI).

In the realm of steel production, Lieber, Stolpe, Konrad, et al. [33] have done exemplary work with their study and presentation. There is a suggestion for automating the process of preparing value series data, which should improve both the operation's efficiency and the quality of the outputs. This research demonstrates the promising future of AI/ML techniques for improving manufacturing quality control. It is possible that with the right use of AI/ML technology, a new generation of intelligent manufacturing may emerge that excels in all aspects of a sustainable process, from supply chain management and quality control to predictive maintenance and energy efficiency.

Table 1provides an overview of the primary domains, major goals, and primary AI/ML applications in sustainable manufacturing.

Main Areas in Sustainable Manufacturing	Key Objective	AI/ML Applications
Supply Chain Management	Ready product available in the appropriate place at a specific time	Improves transparency, accelerates decision-making, and produces accurate demand forecasting
Quality Control	Recognize the early signs of potential production failures within the shortest terms in order to save resources and sustain operational efficiency	Improves the response time and allows eliminating possible failures
Predictive Maintenance	Detects possible production malfunctions that may cause product quality issues	Creates accurate forecasts as to when the machinery must be repaired
Energy consumption	Recommendations that will strike a balance in energy use	Improves excessive use of certain materials, redundant production scrap waste, inefficient supply chain management, logistics, and unequal distribution of energy resources

More theoretical and practical investigation into the interplay of I.4 technologies, AI/ML, and long-term viability is required. This claim is supported by research that identifies the so-called Fourth Industrial Revolution (composed of AI and other digital technologies) as one of the six transformations necessary to achieve the sustainable development goals [34], and was published in Nature Sustainability by Columbia University Earth Institute director Jeffrey Sachs and several other experts.

CONCLUSION

The authors of this study chose to examine the literature on what has recently become a very popular area of study in the scientific community: the current state of the art of AI and ML applications. There is a great deal of information out there on any given topic, and it can be difficult, if not impossible, to read everything that's ever been written about it. That's why we adopted a methodical approach to selecting the most pertinent material. This document provides a comprehensive overview of the use of ML methods across a wide range of scientific disciplines. Documents were chosen using transparent and objective inquiry techniques that did not depend on the expertise of the researchers. Among its goals, the publication sought to give a thorough framework on the literature on the research of AI and ML as well as a jumping-off point for integrating knowledge through research in this area and to recommend future research pathways. Note that only WoS and Scopus were used to compile this document, and that only open-access materials were considered for inclusion. So, there are a lot of restricted-access papers and other indexing databases like Google Scholar that could be combined in the future for research.

REFERENCES

1. Ghasemi, Y.; Jeong, H.; Choi, S.H.; Park, K.-B.; Lee, J.Y. Deep learning-based object detection in augmented reality: A systematic review. Comput. Ind. 2022, 139, 103661. [CrossRef]

2. Widdows, D.; Kitto, K.; Cohen, T. Quantum mathematics in artificial intelligence. J. Artif. Intell. Res. 2021, 72, 1307–1341. [CrossRef]

3. Izonin, I.; Tkachenko, R.; Peleshko, D.; Rak, T.; Batyuk, D. Learning-based image super-resolution using weight coefficients of synaptic connections. In Proceedings of the 2015 Xth International Scientific and Technical Conference "Computer Sciences and Information Technologies"(CSIT), Lviv, Ukraine, 14–17 September 2015; pp. 25–29

4. Adopting, Deploying, and Applying AI. Available online: https://www.mckinsey.com/featured-insights/artificial-intelligence/ ai-adoption-advances-but-foundational-barriers-remain (accessed on 21 April 2022)

5. Artificial Intelligence. Available online: https://www.britannica.com/technology/artificial-intelligence (accessed on 21 April 2022).

6. Everitt, T.; Goertzel, B.; Potapov, A. Artificial general intelligence. In Lecture Notes in Artificial Intelligence; Springer: Berlin/Heidelberg, Germany, 2017.

7. Szczepanski, M. Economic Impacts of Artificial Intelligence (AI). 2019. EPRS: European Parliamentary Research Service. Available online: https://policycommons.net/artifacts/1334867/economic-impacts-of-artificial-intelligence-ai/1940719/ (accessed on 27 May 2022).

8. Ogidan, E.T.; Dimililer, K.; Ever, Y.K. Machine learning for expert systems in data analysis. In Proceedings of the 2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), Ankara, Turkey, 19–21 October 2018; pp. 1–5.

9. 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.

10. The Socio-Economic Impact of AI in Healthcare, October 2020. Available online: https://www.medtecheurope.org/wp-content/ uploads/2020/10/mte-ai_impact-in-healthcare_oct2020_report.pdf (accessed on 21 April 2022).

11. Adopting, Deploying, and Applying AI. Available online: https://www.mckinsey.com/featured-insights/artificial-intelligence/ ai-adoption-advances-but-foundational-barriers-remain (accessed on 21 April 2022)

12. Haseeb, M.; Mihardjo, L.W.; Gill, A.R.; Jermsittiparsert, K. Economic impact of artificial intelligence: New look for the macroeconomic assessment in Asia-Pacific region. Int. J. Comput. Intell. Syst. 2019, 12, 1295.

13. Financial Climate in the Republic of Kazakhstan. Available online: https://www2.deloitte.com/kz/ru/pages/about-deloitte/ articles/financial_climate_in_kazakhstan.html (accessed on 21 April 2022).

14. Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan. Available online: https://stat.gov.kz/search (accessed on 21 April 2022).

15. Lu, H.; Li, Y.; Chen, M.; Kim, H.; Serikawa, S. Brain intelligence: Go beyond artificial intelligence. Mob. Netw. Appl. 2018, 23, 368–375. [CrossRef]

16. Mukhamediev, R.I.; Symagulov, A.; Kuchin, Y.; Zaitseva, E.; Bekbotayeva, A.; Yakunin, K.; Assanov, I.; Levashenko, V.; Popova, Y.; Akzhalova, A. Review of Some Applications of Unmanned Aerial Vehicles Technology in the Resource-Rich Country. Appl. Sci. 2021, 11, 10171

17. Peres, R.S.; Jia, X.; Lee, J.; Sun, K.; Colombo, A.W.; Barata, J. Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook. IEEE Access 2020, 8, 220121–220139

18. Imagenet. Available online: http://image-net.org/index (accessed on 21 April 2022).

19. Nikolenko, S.I. Synthetic Data for Deep Learning; Springer: Berlin/Heidelberg, Germany, 2021.

20. Anderson, R.N., 2017. December. 'Petroleum Analytics Learning Machine'for optimizing the Internet of Things of today's digital oil field-to-refinery petroleum system. In: Proceedingsin 2017 IEEE International Conference on Big Data (Big Data), pp. 4542e4545.

21. Temizal, C., Canbaz, C.H., Palabiyik, Y., Putra, D., Asena, A., Ranjith, R., Jongkittinarukorn, K., 2019. A comprehensive review of smart/intelligent

oilfield technologies and applications in the oil and gas industry. In: Proceedings in Society of Petroleum Engineers. SPE-195095-MS.

22. Evans, S.J., 2019. How digital enegineering and cross- induatsry knowledge tranfer is reducing project execution risks in oil and gas. In: Proceedings in Offshore Technology Conference Held in Houston, Texas, USA, 6 e 9 May 2019, OTC29458-MS.

23. Anifowose, F.A., Labadin, J., Abdulraheem, A., 2017a. Ensemble machine learning: an untapped modeling paradigm for petroleum reservoir characterization. J. Petrol. Sci. Eng. 151, 480e487.

24. Ani, M., Oluyemi, G., Petrovski, A., Rezaei-Gomari, S., 2016. Reservoir uncertainty analysis: the trends fromProbability to algorithms and machine learning. In: Proceedings of the SPE Intelligent Energy InternationalConference and Exhibition. Aberdeen, UK, 6e8 September 2016.

25. Rana, S., Ertekin, T., King, G.R., 2018. An efficient probabilistic assisted history matching tool using GaussianProcesses proxy models: application to coalbed methane reservoir. In: Proceedings of the SPE AnnualTechnical Conference and Exhibition, Dallas, TX, USA, 24e26 September 2018.

26. Esmaili, S., Shahab, D., 2016. Full field reservoir modeling of shale assets using advanced data-driven analytics. Geosci. Front. 7, 11e20.

27. Sami, N.A., Ibrahim, D.S., 2021. Forecasting mult multiphase flowing bottom-hole pressure of vertical oil wells using three machine learning techniques. Petroleum Research 1e6.

28. Hazbeh, O., Aghdam, S.K., Ghorbani, H., Mohamadian, N., Alvar, M.A., Moghadasi, J., 2021. Comparison of accuracy and computational performance between the machine learning algorithms for rate of penetration in directional drilling well. Petroleum Research 1e12.

29. Hassanvand, M., Moradi, S., Fattahi, M., Zargar, G., Kamari, M., 2018. Estimation of rock uniaxial compressive strength for an Iranian carbonate oil reservoir: modeling vs. artificial neural network application. Petroleum Research 3 (4), 336e345.

30. Priyanka, E.B., Thangavel, S., Gao, X.Z., 2021. Review analysis on cloud computing based smart grid technology in the oil pipeline sensor network system. Petroleum Research 6 (1), 77e90.

31. Lu, H., Huang, K., Azimi, M., Guo, L., 2019. Blockchain technology in the oil and gas industry: a review of applications, opportunities, challenges, and risks. IEEE Access 7, 41426e41444.

32. Gupta, N.A. Literature Survey on Artificial Intelligence. 2017. Available online: https://www.ijert.org/research/a-literature-survey-on-artificial-intelligence-IJERTCONV5IS19015.pdf (accessed on 7 January 2020).

33. Lieber, D.; Stolpe, M.; Konrad, B.; Deuse, J.; Morik, K. Quality prediction in interlinked manufacturing processes based on supervised & unsupervised machine learning. Procedia CIRP 2013, 7, 193–198.

34. Sachs, J.D.; Schmidt-Traub, G.; Mazzucato, M.; Messner, D.; Nakicenovic, N.; Rockström, J. Six Transformations to Achieve the Sustainable Development Goals. Nat. Sustain. 2019, 2, 805–814.