Restrictions, Challenges and Opportunities for AI and ML

Shaker Mahmood Mayo[1]
[1]*University of Engineering and Technology Lahore
*** Email**: plannershaker@uet.edu.pk

Citation | Mayo.S.M "Restrictions, Challenges and Opportunities for AI and ML", International Journal of Innovations in Science & Technology, Vol. 5, No. 2, pp. 121-132, June 2023
Received| April 20, 2023**; Revised|** May 22, 2023**; Accepted|** June 04, 2023; **Published|** June 05, 2023.

Artificial intelligence (AI) refers to a collection of techniques that are being developed to address a wide variety of practical problems. Machine learning (ML) is the backbone of artificial intelligence (AI), comprising a suite of algorithms and techniques designed to solve the issues of categorization, clustering, and prediction. There are bright prospects for putting AI and ML to use in the real world. As a result, there is a lot of study being done in this field. However, mainstream adoption of AI in industry and its widespread use in society are still in their infancy. For understanding the obstacles involved with mainstream AI implementations, both the AI (internal problems) and societal (external problems) viewpoints are required. With this in mind, we can determine what has to happen first to get AI technology into the hands of industry and the public. 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. This methodical approach makes it possible to define institutional, human resource, societal, and technological constraints. This paper provides a roadmap for future research in artificial intelligence and machine learning that will help us overcome current obstacles and broaden the range of these technologies' potential uses.

Keywords: AI, ML, Restriction, Opportunities

Introduction

Research and development in the area of artificial intelligence (AI) is progressing and is the subject of debates among experts. Research in AItakes into account both the theoretical foundations of AI systems and their practical implementations across a wide range of societal domains. Artificial intelligence approaches include machine learning (ML) algorithms that enable the prediction of novel data attributes using previously identified properties in training data[1]. Deep learning (DL) is a subfield of machine learning. There has been a rise in study of this topic in recent years[2]. The quantity of papers archived in academic libraries provides evidence of this. [3]. There are many real-world applications of AI techniques. frequently explored in the scientific literature [4][5]. Research in AI, ML, and DL is mostly concentrated in the fields of computer science, engineering, and mathematics [6].

Computer science encompasses a wide range of topics. Image and signal Processing , signal analysis[4] , natural language processing , security , and intelligent software and hardware are all examples of intelligent software and hardware. Design are just some of the many areas where this study has been put to use. These studies are predicated on AI, ML, and DP methods like data clustering [5], data visualization, and others. These methods have been useful in many fields besides computer science. AI has been proved beneficial for industries including banking [6], finance, and logistics. Most of these studies[7], however, focus on the potential uses of AI. We hope to address some of the challenges that have been raised by the widespread adoption of AI and ML in the workplace and daily life. A methodical examination of AI and ML allows for the detection and evaluation of such challenges. These studies allow us to consider the classification of AI and ML technologies, the relationship between AI and ML approaches, and the prospective applications of these technologies.

As demonstrated by resource-based economies[8], systematic analysis of AI and ML is important for revealing the issues connected with these domains. The implementation of cutting-edge technologies has the potential to dramatically boost the efficiency of economic spheres [17,18]. The extraction of minerals is crucial to the regional economies of countries that are wealthy in natural resources. However, their actual reserves are quickly dwindling. Economic exploitation of various resources of the area (agricultural goods, animal husbandry, new mineral deposits, human reserves, etc.) is essential to the sustainable development concept. The low adoption rate of modern technology leads to lower productivity, the growth of low-value-added businesses, and the stagnation of those with the potential to produce high value-added goods and services[9].

Only 1% of businesses are considered to be in the high-tech industry, while the share of innovative products is only 1.6% [10]. There is a discrepancy between labor productivity in different economic sectors. The disparity in agriculture is 12-15 times larger than in nations like Australia and Canada, mining is 5-10 times larger, and manufacturing is 2-4 times larger. Because of a drop in gross fixed capital creation from 30% of GDP in 2007 to 23.3% in 2016, contemporary technology adoption[11], development, and depreciation, as well as the technological sophistication of fixed assets, act as brakes on productivity growth. Most exports are made up of primary products [12].

Artificial intelligence (AI) is, without a question, a powerful tool in this respect. Artificial intelligence has a substantial impact on the economy in sectors like healthcare, retail, transportation, logistics, automated production, banking, and more[13]. Many nations are either formulating or enacting plans to advance AI in their own ways[14].

Quantitative indicators of these shifts, derived using the methodology of and the corpus of texts described in [15], show that the percentage of media publications devoted to AI is on the rise, reaching as high as 5% of media publications and as high as 1% of media publications in Russia.

Although widespread use of AI has some encouraging potential, doing so will require a fresh wave of technological innovation and progress in artificial intelligence and widening use of the technology[16]. This study aims to systematize artificial intelligence, addressing both the foundational technologies of AI and the barriers to implementing AI in economies across all types of resources.

Classification of ML and AI

"Perform tasks commonly associated with intelligent beings" [17] is something an AI-enhanced digital computer or computer-controlled robot can do. Artificial intelligence (AI) also includes the software and hardware techniques that attempt to mimic or copy human behavior and thought. Artificial intelligence is often classified as either weak AI, strong AI, or general AI[18], based on the system's "degree of intelligence" in comparison to a human. Today's practical applications make use of weak or soft AI since it may be trained to solve specific problems with a satisfactory degree of precision. The study's emphasis is on generally applicable AI. Natural Language Processing (NLP), speech synthesis, Machine learning, and text, planning, and computer vision, robotics, expert systems are all subfields of AI. [19].

Machine learning has been quite helpful in both the academic and professional worlds. For instance, we consider the ML application criteria and the possibility of deep learning [20] while tackling chemistry-related problems. Different fields have found applications for ML, but not limited to the following: Medical imaging, astronomy, computational biology agriculture , municipal economy and industry [21], building , modeling environmental and geo-ecological processes, petrographic investigations exploration , and mining are some of the fields covered. The usage of ML is widespread, and it is at the forefront of current NLP research [22].

Methods in machine learning (ML) can be broken down into several categories based on the type of learning involved and the goal of the algorithm, supervised learning (SL) [23], unsupervised learning (UL) or cluster analysis, dimensionality reduction (DR), semi-supervised learning (SSL), reinforcement learning (RL), and deep learning (DL). When applied to a set of unlabeled items, UL techniques automate the process of sorting the objects into distinct categories based on their characteristics. Through UL, we are able to see anomalies, imbalances, and previously unseen patterns in data.

Classification and regression problems are addressed by SL techniques. Such issues occur if a finite number of uniquely marked items must be distributed across an infinite pool of items. The classification problem is realized if the objects are labeled with a finite collection of integers (class numbers). Using this set as an example, the classification algorithm will assign one of the indicated numbers to the unlabeled objects. Using integer and fractional real values to label objects solves the regression recovery problem. For unlabeled items, the algorithm chooses a real number based on labeled items. Predictive or information-gap-filling issues are addressed here.

DL Deep Learning approaches tackle the problem of revealing hidden characteristics in data arrays by employing neural networks with a large number of hidden layers and networks with a unique architecture. The term "transfer learning" (TF) is frequently used while discussing DL. "Transfer Knowledge" (TF) implies to "help a learner in one domain by giving them knowledge of a related domain" [24]. Conditional classification of ML models into the classical and current categories but it does include some of the most common types of traditional SL models: k-NN, logistic regression , decision tree [DT], support vector machines [SVM] [25], and feed forward artificial neural networks [ANN]. k-means and Principal Component Analysis (PCA) are two examples of the traditional UL models[26].

When it comes to artificial intelligence (AI), deep learning is the most rapidly expanding field [27]. Deep learning (DL) is a collection of techniques that make use of neural networks with multiple hidden layers. The capacity of deep architectures to tackle challenges utilizing an end-to-end approach is arguably their greatest strength. This method avoids the need for preliminary data processing because a signal or picture vector is used as an input to the network and the network autonomously determines the regularities relating the input vector to the goal variable. Choosing important features is a time-consuming and tough endeavor, but the network does it for you. The research process is substantially facilitated by the network's functionality. These benefits, however, only materialize with enough training data and the right neural network architecture.

For sorting data, the many-to-one structure is employed. One example is the text's sentiment or tone (sentiment analysis). Not only do individual words and word combinations determine the text's tone, which can be stated through a categorical evaluation (neutral, negative, positive), but word choice also matters. Named entity recognition is another activity that needs to be completed. Named entities include proper names, days of the week and months, locations, dates, and so on. The nucleotide sequence is also important in DNA analysis [28]since it establishes the value of a gene [29].

Transformer models that emerged as a result of the evolution of the RNN concept include LSTM, BERT (bidirectional encoder representations from transformers), ELMO, GPT (generate pre-trained transformer), and generative adversarial networks are all examples of generative adversarial networks. These models have recently acquired prominence due to their ability to tackle natural language processing challenges. The complicated regularities in the supplied data can be isolated with the help of convolutional neural networks (CNNs), and these regularities are independent of their position in the input signal vector. Lines in the image, both horizontal and vertical, and other visual cues serve to illustrate them.
During network training, convolutional filters are created by fine-tuning the weights of the neurons representing the filter.

The convolution procedure keeps the training process's computing complexity under control. CNNs have excelled in the realm of image processing. For image classification, the LeNet model [30] was the first to use convolutional filters, pooling, and a fully connected neural network (FC), and it sparked the creation of this architecture of deep neural networks. There are two fully linked layers and four convolutional layers in this network.

By extending the network size and implementing the maxpool, AlexNet [31] is an improvement on the original architecture. There are almost 100 times as many weights in this network as there are in LeNet. To guarantee the identification of unusual features, GoogleNet employs the so-called inception module, which creates parallel routes for convolutional filters of varying sizes. ResNet is a 152-layer network that uses residual modules to address the vanishing gradient problem [32]. When applied to the issues of image segmentation (the Unet model and identification and recognition ("in one pass") (the Yolo model , convolutional filters proved to be a successful tool.

Self-attention methods (so-called transformer architecture) have recently been applied to CV tasks, resulting in significant gains. Models using this method, such as Florence[33], Swin Transfomer V2 , and DINO, have obtained SotA results on certain object classification tasks. Graph neural networks (GNNs), a subtype of deep learning algorithms that are specifically built to do inference on graph-based data. Convolutional neural networks, which are commonly used to process two-dimensional black-and-white and three-dimensional color picture data, can be thought of as a graph-structured data generalization of this technique.

These function well in structural scenarios involving chemicals, physical systems, knowledge graphs, social networks, and other applications where the graph structure is clear. However, they can also be used efficiently in non-structural circumstances, like as when generating a fully-connected "word" graph for text or a scene graph for an image, when graphs are implicit and must be generated from the job itself [34].

Classifying.

We can define the potential of AI and ML to proposed categorization of these technologies. The proposed categorization of AI and ML tools allows us to determine their strengths and weaknesses. RNN and CNN-based DL techniques are undergoing rapid innovation right now [35]. Recognition, recommendations , NLP , data processing , tracking or monitoring , personalization [36], and learning are just some of the most common challenges that these and other technologies are used to. The use of fuzzy logic [37], route sets , and possibility conception-based theories are frequently elaborated in AI applications for the interpretation of ambiguous data. However, it is important to examine the potential of AI growth from a variety of angles. In addition, the potential applications of AI could constitute an early viewpoint [38]. The majority of AI research is done in the sectors of healthcare agriculture and academics [39]. It is projected, however, to accelerate the deployment of AI techniques in areas such as social applications, the home, and the arts. Industry 4.0 trends, in which AI technologies serve as the foundation for the majority of applications, are both a cause and a result of the potential given by AI. Based on unsupervised approaches to uncertain data , it leads to considerable research and deployment of AI in safety, cyber security, and IoT [40].

Limitations

The future of artificial intelligence seems bright. The potential financial benefits of applying AI are often regarded as promising. An estimated 200 billion Euros in economic damage has been done to the European healthcare system[41][42]. The effect has been linked to a reduction in response time and an increase in lives saved. The outcomes of AI application in diverse economic sectors are carried out in refs. The mining, processing, and shipping of raw materials accounts for around a quarter of GDP.

Approximately 75% of all exports are made up of primary goods. Only 1% of businesses are considered to be cutting edge, despite the fact that innovative items account for 1.6% of GDP. As a result, it is expected that the application of AI technology will lead to a 1.5-2% boost in GDP[43]. However, there are a number of challenges, and resolving them would open up new opportunities for the application of AI in manufacturing and spur further advances in AI technology.

The technical and non-engineering communities typically research and consider the external AI concerns. These restrictions may be imposed at any tier of AI administration, from the central government down to a single bureau. These issues are interconnected, thus the solutions will likely be difficult to figure out[44]. Multifaceted difficult challenges include, for example, social restrictions such as ethical, moral, and legal issues, as well as organizational constraints such as a lack of an artificial intelligence adoption strategy and a fragile technology infrastructure. It is frequently vital for the government to consider such constraints as national strategies. The European Union's (EU) Ethics Guidelines for Trustworthy AI is one such plan, which encourages governments to foster AI research and development by providing a favorable policy climate and adopting national policies for AI applications. Building out support systems for AI is a crucial part of putting these plans into action. There are internal and social benefits to building this infrastructure as well[45].

To begin, it involves data collecting alongside safeguards and cyber protections [46]. Furthermore, infrastructure development decisions might be made at the level of a single business or academic institution [46]. In a similar vein, the government and each individual company both have a role to play in resolving the people issues they face. Lack of competence, lack of management buy-in, and a society not sufficiently saturated with the interests and realities of AI all contribute to the constraints of the personnel[47].

Educating workers about AI's potential applications is a government responsibility that might begin in secondary institutions. Incorporating AI components into online training courses increases access to low-cost education while also raising educational standards and bolstering the job market. While all external constraints must be taken into account, the economic ones are particularly weighty. Evidence for this comes from research on the correlation between a country's level of economic development and its readiness to implement AI[48] .

Studies on AI, ML, and DL frequently explore the technical limitations of these technologies. In order to collect data in several fields, including medicine, agriculture, and others, specialized infrastructures like biobanks are developed[49]. Feature extraction and/or dimensionality reduction are frequently used as the foundations for the preliminary transformation techniques. There are studies looking into how to speed up the learning process and how to make results readily available. The advancement of new fuzzy based methodologies has removed the barriers that previously existed in artificial intelligence technology[50]. Reduces the degree to which we must speculate about the results. The study's authors would like to draw attention to certain important limitations of economy based on scarce resources to the wider AI limits.

Mining and processing the extracted materials accounts for a significant portion of the GDP in resource-based economies, as previously mentioned[51]. These methods are founded on the imported technology that are commonly used. Because borrowing inventions from other countries requires far less effort, these economies do not support the development of technology within their own borders. Often, these countries lack the prerequisites (stable ICT infrastructure, human resources, and a legislative framework) needed to collect enough data to use AI algorithms for development. Existing data are often ignored because they are either unavailable, arrive too late or not at all, are not digitized, or lack the granularity necessary to inform decisions and spur new developments in the field[52].

Therefore, economic benefits gained from the use of the AI should be limited in some ways. The impact of AI and ML technologies, , can be greatly amplified by increasing the proportion of high-tech output[53]. Progress in using big data and the analytical capability of AI is commonly emphasized in the development areas of agriculture, healthcare, and education. Therefore, resource-based economies should put a premium on developing these areas [54].

The current technology presents a substantial barrier to the widespread adoption of AI in the manufacturing and service sectors, notwithstanding the high hopes attached to its application. Some inherent difficulties with utilizing AI technologies necessitate careful thought and appraisal of the likelihood of overcoming these constraints[55].

Producing training data for deep machine learning models. Numerous issues in deep learning can't be fixed unless more and better data sets (data set—DS) are collected and analyzed.

However, the currently prevalent datasets may be insufficient for resolving certain challenges; for example, they may only recognize a limited collection of objects. As a result, the data scarcity problem in computer vision can be addressed by using synthetic DS generated by 3D graphic editors, gaming engines, and surroundings [56]. These DS are particularly useful in the training of unmanned vehicles. Synthetic datasets have a wide range of applications. They have recently been generated using generative adversarial networks [57].

The pace of education must be increased. The transfer learning strategy allows for the use of previously trained models to speed up the learning process when the domain and the problem are near to the existing solutions. This means that one or more layers can be added to a neural network that has already been trained on a huge dataset[58]. At the end of training, a smaller, more specific data set is used to fine-tune the additional layers. All other layers are treated as "frozen" and their relative weights are fixed. The initial trained network is thought to remember the fundamental patterns that are specific to a given data set (faces, landscapes, speech, etc.), and subsequent layers zero in on the specifics of that data set. By utilizing transfer learning, not only is the learning process sped up, but the hardware requirements are also lowered. Due to the rapid advancement of machine learning, artificial intelligence (AI) has recently seen tremendous success[59].

However, a "black box" approach to education is not without its dangers. Non-linear classification and especially deep learning models lack transparency, making it difficult to comprehend how the model made a given conclusion, in contrast to some traditional machine learning methods like decision trees. This is a major issue that prevents AI from being widely used in healthcare, finance, and other fields[60].

As the "black box" that it is, a complicated machine learning model obscures the underlying logic behind its outputs. The "black box" can be made "white" or "grey" by employing techniques that allow for the evaluation of the impact of input parameters on the output[61]. Model type, data type, explanation scope, and explanation aim are the four categories of explanation strategies used today. In many cases, it is preferable to have an interpreter who is unattached to the machine learning model; that is, the interpreter should be agnostic and provide both local and global interpretations[62]. Some of these issues have been addressed by recently developed techniques such as interpretable model-agnostic (LIME) and SHapley Additive exPlanations (SHAP). However, in case of elaborate models with strong property correlation, their implementation can be challenging due to the linear character of the interpretation (LIME) and the high complexity of the calculations (SHAP)[63].

Furthermore, if the parameters are well-defined, their effects can be understood, both individually and in combination[64]. Otherwise, parameters that lack semantic clarity would render such an interpretation meaningless [65] [66]. To fully integrate AI&ML into the economy, these challenges must be addressed;

There has been an uptick in publication volume, which indicates that researchers are working hard to address the shortcomings of existing AI systems[67] [68] [69].

Conclusions:

Deep learning and artificial intelligence study is expanding the most quickly. Practical implementations of previously proposed networks and new findings arise on a near-daily basis. Networks for recognizing text, voice, and handwriting, transforming and styling images, and processing time sequences are all part of this broad field of study and practical application. However, there are obstacles to applying AI&ML, both in terms of the technologies themselves and in a socioeconomic environment that may not be prepared for the rapid changes. The purpose of this research is to start standardizing AI's several subfields. Furthermore, we classified the barriers to implementing AI technology, particularly in resource-based economies. The application of AI&ML techniques is hampered by both technical limitations inherent in the technology and external factors such as the structure of an organization's operations and data collection, as well as psychological issues related to an inability to comprehend the workings of machine learning models.

The scientific community is attempting to enhance AI models, accelerate learning, and overcome other technological limitations, such as a shortage of data for deep learning. As seen by the increasing volume of scholarly papers, scholars are becoming increasingly busy. Some technological concerns are expected to be rectified in the near future. Techniques for collecting data sets, explaining the findings of machine learning systems, and speeding up the learning process are all well-established and widely used in various contexts. However, for the great majority of AI applications, we still require solutions to the difficulties highlighted. These characteristics are especially important in industries where widespread AI adoption could have far-reaching economic and social effects. The integration of remote sensing and machine learning technology could benefit soil quality, salinity, and agricultural output. Future research should focus on collecting and making large data sets widely accessible, implementing existing technologies, and providing solutions to actual issues in industries such as mining, transportation, trade, banking, healthcare, and so on.

References

[1] L. Mou, P. Ghamisi, and X. X. Zhu, "Deep recurrent neural networks for hyperspectral image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 7, pp. 3639–3655, 2017, doi: 10.1109/TGRS.2016.2636241.

[2] T. J, de Silva V, and L. J, "A global geometric framework for nonlinear dimensionality reduction," *Science (80-.).*, vol. 290, no. December, pp. 2319–2323, 2000.

[3] A. Sanenga, G. A. Mapunda, T. M. L. Jacob, L. Marata, B. Basutli, and J. M. Chuma, "An overview of key technologies in physical layer security," *Entropy*, vol. 22, no. 11, pp. 1–34, 2020, doi: 10.3390/e22111261.

[4] W. N. Hussein, L. M. Kamarudin, H. N. Hussain, A. Zakaria, R. Badlishah Ahmed, and N. A. H. Zahri, "The Prospect of Internet of Things and Big Data Analytics in Transportation System," *J. Phys. Conf. Ser.*, vol. 1018, no. 1, 2018, doi: 10.1088/1742-6596/1018/1/012013.

[5] D. Mhlanga, "Industry 4.0 in finance: the impact of artificial intelligence (ai) on digital financial inclusion," *Int. J. Financ. Stud.*, vol. 8, no. 3, pp. 1–14, 2020, doi: 10.3390/ijfs8030045.

[6] R. S. Peres, X. Jia, J. Lee, K. Sun, A. W. Colombo, and J. Barata, "Industrial Artificial Intelligence in Industry 4.0 -Systematic Review, Challenges and Outlook," *IEEE Access*, pp. 220121–220139, 2020, doi: 10.1109/ACCESS.2020.3042874.

[7] M. H. Jarrahi, "Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making," *Bus. Horiz.*, vol. 61, no. 4, pp. 577–586, 2018, doi: 10.1016/j.bushor.2018.03.007.

[8] W. Wang and K. Siau, "Artificial intelligence, machine learning, automation, robotics,

future of work and future of humanity: A review and research agenda," *J. Database Manag.*, vol. 30, no. 1, pp. 61–79, 2019, doi: 10.4018/JDM.2019010104.
[9] D. Kim *et al.*, "Review of machine learning methods in soft robotics," *PLoS One*, vol. 16, no. 2 February, pp. 1–24, 2021, doi: 10.1371/journal.pone.0246102.
[10] M. A. Kilian, M. Kattenbeck, M. Ferstl, B. Ludwig, and F. Alt, "Towards task-sensitive assistance in public spaces," *Aslib J. Inf. Manag.*, vol. 71, no. 3, pp. 344–367, 2019, doi: 10.1108/AJIM-07-2018-0179.
[11] S. Khan, A. Khan, M. Maqsood, F. Aadil, and M. A. Ghazanfar, "Optimized Gabor Feature Extraction for Mass Classification Using Cuckoo Search for Big Data E-Healthcare," *J. Grid Comput.*, vol. 17, no. 2, pp. 239–254, 2019, doi: 10.1007/s10723-018-9459-x.
[12] A. Mosavi and A. Varkonyi, "Learning in Robotics," *Int. J. Comput. Appl.*, vol. 157, no. 1, pp. 8–11, 2017, doi: 10.5120/ijca2017911661.
[13] Y. Lecun and K. Kavukcuoglu, "IEEE Xplore - Convolutional networks and applications in vision", [Online]. Available: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5537907
[14] Z. Liu *et al.*, "Swin Transformer V2: Scaling Up Capacity and Resolution," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2022-June, pp. 11999–12009, 2022, doi: 10.1109/CVPR52688.2022.01170.
[15] Yoav Goldberg, "A Primer on Neural Network Models for Natural Language Processing," *J. Artif. Intell. Res.*, vol. 57, pp. 345–420, 2016, [Online]. Available: http://www.jair.org/papers/paper4992.html
[16] J. P. Usuga Cadavid, S. Lamouri, B. Grabot, R. Pellerin, and A. Fortin, "Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0," *J. Intell. Manuf.*, vol. 31, no. 6, pp. 1531–1558, 2020, doi: 10.1007/s10845-019-01531-7.
[17] MacQueen, James and others, "Some methods for classification and analysis of multivariate observations," *Proc. fifth Berkeley Symp. Math. Stat. Probab.*, vol. 1, no. 14, pp. 281–297, 1967, [Online]. Available: http://books.google.de/books?hl=de&lr=&id=IC4Ku_7dBFUC&oi=fnd&pg=PA281&dq=MacQueen+some+methods+for+classification&ots=nNTcK1IdoQ&sig=fHzdVcbvmYJ-lTNHu1HncmOFOkM#v=onepage&q=MacQueen some methods for classification&f=false
[18] Y. I. Kuchin, R. I. Mukhamediev, and K. O. Yakunin, "One method of generating synthetic data to assess the upper limit of machine learning algorithms performance," *Cogent Eng.*, vol. 7, no. 1, 2020, doi: 10.1080/23311916.2020.1718821.
[19] Y. Motai, N. A. Siddique, and H. Yoshida, "Heterogeneous data analysis: Online learning for medical-image-based diagnosis," *Pattern Recognit.*, vol. 63, no. September 2016, pp. 612–624, 2017, doi: 10.1016/j.patcog.2016.09.035.
[20] C. A. Hidalgo and R. Hausmann, "The building blocks of economic complexity," *Proc. Natl. Acad. Sci. U. S. A.*, vol. 106, no. 26, pp. 10570–10575, 2009, doi: 10.1073/pnas.0900943106.
[21] G. Plastiras, C. Kyrkou, and T. Theocharides, "Efficient convnet-based object detection for unmanned aerial vehicles by selective tile processing," *ACM Int. Conf. Proceeding Ser.*, 2018, doi: 10.1145/3243394.3243692.
[22] M. Macas and C. Wu, "Review: Deep Learning Methods for Cybersecurity and Intrusion Detection Systems," *Proc. - 2020 IEEE Latin-American Conf. Commun. LATINCOM 2020*, pp. 1–6, 2020, doi: 10.1109/LATINCOM50620.2020.9282324.
[23] N. Artrith *et al.*, "Best practices in machine learning for chemistry To cite this version : HAL Id : hal-03243917 Best practices in machine learning for chemistry," 2021.
[24] G. Ros, L. Sellart, J. Materzynska, D. Vazquez, and A. M. Lopez, "The SYNTHIA Dataset: A Large Collection of Synthetic Images for Semantic Segmentation of Urban Scenes," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2016-Decem, no. 600388, pp. 3234–3243, 2016, doi: 10.1109/CVPR.2016.352.
[25] G. Nguyen *et al.*, "Machine Learning and Deep Learning frameworks and libraries for large-

scale data mining: a survey," *Artif. Intell. Rev.*, vol. 52, no. 1, pp. 77–124, 2019, doi: 10.1007/s10462-018-09679-z.
[26] H. F. Yu, F. L. Huang, and C. J. Lin, "Dual coordinate descent methods for logistic regression and maximum entropy models," *Mach. Learn.*, vol. 85, no. 1–2, pp. 41–75, 2011, doi: 10.1007/s10994-010-5221-8.
[27] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," *Sensors (Switzerland)*, vol. 18, no. 8, pp. 1–29, 2018, doi: 10.3390/s18082674.
[28] G. Van den Broeck, A. Lykov, M. Schleich, and D. Suciu, "On the Tractability of SHAP Explanations," *J. Artif. Intell. Res.*, vol. 74, pp. 851–886, 2022, doi: 10.1613/jair.1.13283.
[29] D. Widdows, K. Kitto, and T. Cohen, "Quantum Mathematics in Artificial Intelligence," *J. Artif. Intell. Res.*, vol. 72, pp. 1307–1341, 2021, doi: 10.1613/JAIR.1.12702.
[30] A. B. Nassif, I. Shahin, I. Attili, M. Azzeh, and K. Shaalan, "Speech Recognition Using Deep Neural Networks: A Systematic Review," *IEEE Access*, vol. 7, pp. 19143–19165, 2019, doi: 10.1109/ACCESS.2019.2896880.
[31] M. Duguleană, V. A. Briciu, I. A. Duduman, and O. M. Machidon, "A virtual assistant for natural interactions in museums," *Sustain.*, vol. 12, no. 17, pp. 1–17, 2020, doi: 10.3390/SU12176958.
[32] R. I. Mukhamediev *et al.*, "Classification of negative information on socially significant topics in mass media," *Symmetry (Basel).*, vol. 12, no. 12, pp. 1–23, 2020, doi: 10.3390/sym12121945.
[33] G. Zeng, Y. He, Z. Yu, X. Yang, R. Yang, and L. Zhang, "Preparation of novel high copper ions removal membranes by embedding organosilane-functionalized multi-walled carbon nanotube," *J. Chem. Technol. Biotechnol.*, vol. 91, no. 8, pp. 2322–2330, 2016, doi: 10.1002/jctb.4820.
[34] S. Panigrahi, A. Nanda, and T. Swarnkar, "A Survey on Transfer Learning," *Smart Innov. Syst. Technol.*, vol. 194, pp. 781–789, 2021, doi: 10.1007/978-981-15-5971-6_83.
[35] B. A. Erol, A. Majumdar, P. Benavidez, P. Rad, K. K. R. Choo, and M. Jamshidi, "Toward Artificial Emotional Intelligence for Cooperative Social Human-Machine Interaction," *IEEE Trans. Comput. Soc. Syst.*, vol. 7, no. 1, pp. 234–246, 2020, doi: 10.1109/TCSS.2019.2922593.
[36] T. Tuncer, F. Ertam, S. Dogan, E. Aydemir, and P. Pławiak, "Ensemble residual network-based gender and activity recognition method with signals," *J. Supercomput.*, vol. 76, no. 3, pp. 2119–2138, 2020, doi: 10.1007/s11227-020-03205-1.
[37] C. R. García-Alonso, L. M. Pérez-Naranjo, and J. C. Fernández-Caballero, "Multiobjective evolutionary algorithms to identify highly autocorrelated areas: The case of spatial distribution in financially compromised farms," *Ann. Oper. Res.*, vol. 219, no. 1, pp. 187–202, 2014, doi: 10.1007/s10479-011-0841-3.
[38] L. Zhang, S. Wang, and B. Liu, "Deep learning for sentiment analysis: A survey," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 8, no. 4, 2018, doi: 10.1002/widm.1253.
[39] T. Miller, "Explanation in artificial intelligence: Insights from the social sciences," *Artif. Intell.*, vol. 267, pp. 1–38, 2019, doi: 10.1016/j.artint.2018.07.007.
[40] M. S. Mahdavinejad, M. Rezvan, M. Barekatain, P. Adibi, P. Barnaghi, and A. P. Sheth, "Machine learning for internet of things data analysis: a survey," *Digit. Commun. Networks*, vol. 4, no. 3, pp. 161–175, 2018, doi: 10.1016/j.dcan.2017.10.002.
[41] H. Panetto, B. Iung, D. Ivanov, G. Weichhart, and X. Wang, "Challenges for the Cyber-Physical Manufacturing Enterprises of the Future Université de Lorraine , CNRS , CRAN , France Integration in Manufacturing (IiM) is the first systemic paradigm to organise humans and ma- chines as a whole system , not only at t," 2019.
[42] M. Zitnik, F. Nguyen, B. Wang, J. Leskovec, A. Goldenberg, and M. M. Hoffman, "Machine learning for integrating data in biology and medicine: Principles, practice, and opportunities," *Inf. Fusion*, vol. 50, pp. 71–91, 2019, doi: 10.1016/j.inffus.2018.09.012.

[43] A. L. Barbieri, O. Fadare, L. Fan, H. Singh, and V. Parkash, "Challenges in communication from referring clinicians to pathologists in the electronic health record era," *J. Pathol. Inform.*, vol. 9, no. 1, p. 38, 2018, doi: 10.4103/jpi.jpi.

[44] M. T. Ribeiro, S. Singh, and C. Guestrin, "'Why Should I Trust You?' Explaining the Predictions of Any Classifier," *NAACL-HLT 2016 - 2016 Conf. North Am. Chapter Assoc. Comput. Linguist. Hum. Lang. Technol. Proc. Demonstr. Sess.*, pp. 97–101, 2016, doi: 10.18653/v1/n16-3020.

[45] Y. Wu *et al.*, "Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation," pp. 1–23, 2016, [Online]. Available: http://arxiv.org/abs/1609.08144

[46] S. S. Mousavi, M. Schukat, and E. Howley, "Deep Reinforcement Learning: An Overview," *Lect. Notes Networks Syst.*, vol. 16, pp. 426–440, 2018, doi: 10.1007/978-3-319-56991-8_32.

[47] Y. A. Joo, Y. K. Kim, T. S. Yoon, and K. A. Lee, "Microstructure and High Temperature Oxidation Property of Fe–Cr–B Based Metal/Ceramic Composite Manufactured by Powder Injection Molding Process," *Met. Mater. Int.*, vol. 24, no. 2, pp. 371–379, 2018, doi: 10.1007/s12540-018-0053-3.

[48] M. Müller, V. Casser, J. Lahoud, N. Smith, and B. Ghanem, "Sim4CV: A Photo-Realistic Simulator for Computer Vision Applications," *Int. J. Comput. Vis.*, vol. 126, no. 9, pp. 902–919, 2018, doi: 10.1007/s11263-018-1073-7.

[49] A. Creswell, T. White, V. Dumoulin, K. Arulkumaran, B. Sengupta, and A. A. Bharath, "Generative Adversarial Networks: An Overview," *IEEE Signal Process. Mag.*, vol. 35, no. 1, pp. 53–65, 2018, doi: 10.1109/MSP.2017.2765202.

[50] V. Garcia and J. Bruna, "Few-shot learning with graph neural networks," *6th Int. Conf. Learn. Represent. ICLR 2018 - Conf. Track Proc.*, pp. 1–13, 2018.

[51] S. Lu, Y. Zhu, W. Zhang, J. Wang, and Y. Yu, "Neural Text Generation: Past, Present and Beyond," 2018, [Online]. Available: http://arxiv.org/abs/1803.07133

[52] S. Watanabe *et al.*, "ESPNet: End-to-end speech processing toolkit," *Proc. Annu. Conf. Int. Speech Commun. Assoc. INTERSPEECH*, vol. 2018-Septe, pp. 2207–2211, 2018, doi: 10.21437/Interspeech.2018-1456.

[53] A.-D. Doan, A. M. Jawaid, T.-T. Do, and T.-J. Chin, "G2D: from GTA to Data," pp. 1–9, 2018, [Online]. Available: http://arxiv.org/abs/1806.07381

[54] K. Do, T. Tran, and S. Venkatesh, "Graph transformation policy network for chemical reaction prediction," *Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, pp. 750–760, 2019, doi: 10.1145/3292500.3330958.

[55] J. Agnese, J. Herrera, H. Tao, and X. Zhu, "A survey and taxonomy of adversarial neural networks for text-to-image synthesis," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 10, no. 4, 2020, doi: 10.1002/widm.1345.

[56] A. Barredo Arrieta *et al.*, "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Inf. Fusion*, vol. 58, pp. 82–115, 2020, doi: 10.1016/j.inffus.2019.12.012.

[57] V. Kulkarni, M. Kulkarni, and A. Pant, "Quantum computing methods for supervised learning," *Quantum Mach. Intell.*, vol. 3, no. 2, pp. 1–22, 2021, doi: 10.1007/s42484-021-00050-0.

[58] P. Migkotzidis and A. Liapis, "SuSketch: Surrogate Models of Gameplay as a Design Assistant," *IEEE Trans. Games*, vol. 14, no. 2, pp. 273–283, 2022, doi: 10.1109/TG.2021.3068360.

[59] L. Yuan *et al.*, "Florence: A New Foundation Model for Computer Vision," 2021, [Online]. Available: http://arxiv.org/abs/2111.11432

[60] G. Atherton and L. Cross, "The Use of Analog and Digital Games for Autism Interventions," *Front. Psychol.*, vol. 12, p. 3049, Aug. 2021, doi: 10.3389/FPSYG.2021.669734/BIBTEX.

[61] M. Isabirye, D. V. . Raju, M. Kitutu, V. Yemeline, J. Deckers, and J. Poesen Additional,

"We are IntechOpen , the world ' s leading publisher of Open Access books Built by scientists , for scientists TOP 1 %," *Intech*, p. 13, 2012, [Online]. Available: http://dx.doi.org/10.1039/C7RA00172J%0Ahttps://www.intechopen.com/books/advanced-biometric-technologies/liveness-detection-in-biometrics%0Ahttp://dx.doi.org/10.1016/j.colsurfa.2011.12.014

[62] A. K. Jain, M. N. Murty, and P. J. Flynn, "Data clustering: A review," *ACM Comput. Surv.*, vol. 31, no. 3, pp. 264–323, 1999, doi: 10.1145/331499.331504.

[63] A. Mardani, M. Nilashi, J. Antucheviciene, M. Tavana, R. Bausys, and O. Ibrahim, "Recent fuzzy generalisations of rough sets theory: A systematic review and methodological critique of the literature," *Complexity*, vol. 2017, 2017, doi: 10.1155/2017/1608147.

[64] H. Peng *et al.*, "Large-scale hierarchical text classification with recursively regularized deep graph-CNN," *Web Conf. 2018 - Proc. World Wide Web Conf. WWW 2018*, pp. 1063–1072, 2018, doi: 10.1145/3178876.3186005.

[65] N. Sahadat, N. Sebkhi, and M. Ghovanloo, "Simultaneous multimodal access to wheelchair and computer for people with tetraplegia," *ICMI 2018 - Proc. 2018 Int. Conf. Multimodal Interact.*, pp. 393–399, 2018, doi: 10.1145/3242969.3242980.

[66] J. Lai, J. Qiu, Z. Feng, J. Chen, and H. Fan, "Prediction of Soil Deformation in Tunnelling Using Artificial Neural Networks," *Comput. Intell. Neurosci.*, vol. 2016, 2016, doi: 10.1155/2016/6708183.

[67] Y. Kuchin, R. Mukhamediev, K. Yakunin, J. Grundspenkis, and A. Symagulov, "Assessing the Impact of Expert Labelling of Training Data on the Quality of Automatic Classification of Lithological Groups Using Artificial Neural Networks," *Appl. Comput. Syst.*, vol. 25, no. 2, pp. 145–152, 2020, doi: 10.2478/acss-2020-0016.

[68] J. Hemminghaus and S. Kopp, "Towards Adaptive Social Behavior Generation for Assistive Robots Using Reinforcement Learning," *ACM/IEEE Int. Conf. Human-Robot Interact.*, vol. Part F1271, no. March, pp. 332–340, 2017, doi: 10.1145/2909824.3020217.

[69] F. Tahiru, "AI in education: A systematic literature review," *J. Cases Inf. Technol.*, vol. 23, no. 1, pp. 1–20, 2021, doi: 10.4018/JCIT.2021010101.